Quantum Ai Trading Automated Investing Methodology White Paper

Introduction

Quantum Ai Trading aims to deliver a service that simplifies and automates investing. Quantum Ai Trading offers each investing client a recommended portfolio constructed using Modern Portfolio Theory (MPT) and personalized to their risk tolerance. From there, clients can customize their portfolio using our selection of funds, and Quantum Ai Trading will take care of the rest — reinvesting dividends, rebalancing the portfolio in a tax-efficient way, and performing daily automated Tax-Loss Harvesting.

Quantum Ai Trading 's recommended portfolios are designed to provide an attractive tradeoff between risk and long-term, after-tax, net-of-fee return through a diversified set of global asset classes, each of which is usually represented by a low-cost, passive ETF. This white paper describes the process Quantum Ai Trading uses to construct its recommended portfolios, as well as the ongoing monitoring and rebalancing process, which ensures that all portfolios (recommended and customized) remain close to their target allocations while minimizing taxes from realized gains.

We continuously monitor and periodically rebalance portfolios to ensure they remain optimally diversified. We also attempt to minimize your taxes by analyzing the taxes likely to be generated by each asset class, and creating allocations that are specifically customized for taxable and non-taxable (retirement) portfolios.

Our investment methodology employs five steps:

Identify a diverse set of asset classes

Select the most appropriate ETFs to represent each asset class

Apply Modern Portfolio Theory to construct asset allocations that maximize the expected net-of-fee, after-tax real return for each level of portfolio risk

Determine your risk tolerance to select the allocation that is most appropriate for you

Monitor and periodically rebalance your portfolio, taking advantage of dividend reinvestment to correct deviations from desired weights

Modern Portfolio Theory is one of the most widely accepted frameworks for managing diversified portfolios. The economists who developed MPT, Harry Markowitz and William Sharpe, received the Nobel Prize in Economics in 1990 for their groundbreaking research. While MPT has its limitations, especially in the area of very low probability significant downside scenarios, we and our advisors believe it is the best framework on which to build a compelling investment management service.

Sophisticated investment management services were often available only to wealthy investors through financial advisors. Many of those advisors charge average annual management fees of 1%, and have account minimums of at least $1 million*. By implementing a completely software-based solution, informed by decades of academic research, Quantum Ai Trading is able to deliver its automated investment management service at much lower cost than traditional investment management services.

***PriceMetrix State of Retail Wealth Management, 10th Annual Report, 2020**

Finding Asset Classes

Research consistently has found the best way to maximize returns across every level of risk is to combine asset classes rather than individual securities (Markowitz, 1952; Sharpe, 1964; Brinson, Hood & Beebower, 1986; Brinson, Singer & Beebower, 1991; Ibbotson & Kaplan, 2000). Therefore, the first step in our methodology is to identify a broad set of diversified publicly accessible asset classes to serve as the building blocks for our portfolios. We consider each asset class's long-term historical behavior, risk-return relationship conceptualized in asset pricing theories, and expected behavior based on long-term secular trends and the macroeconomic environment. We also evaluate each asset class's volatility, correlation with the other asset classes, inflation protection, cost to implement via ETF (expense ratio), and tax efficiency.

Asset classes fall under three broad categories: stocks, bonds, and inflation assets. Stocks, despite their high volatility, give investors exposure to economic growth and offer the opportunity for long-term capital growth, and are relatively tax efficient due to the favorable tax treatment (relative to the way ordinary income is taxed) on long-term capital gains and stock dividends. Bonds and bond-like securities are the most important income-producing asset classes. Although bonds have lower return expectations, they provide a cushion for stock-heavy portfolios during economic turbulence due to their low volatility and low correlation with stocks. Most bonds are tax inefficient because bond interest income is taxed at ordinary income tax rates. In taxable accounts, we use Municipal Bonds, whose dividends are exempt from federal income taxes. Assets that protect investors from inflation in both moderate and high inflation environments include Treasury Inflation-Protected Securities (TIPS), Real Estate, and Commodities. Their prices tend to be highly correlated with inflation.

Based on a thorough analysis, our investment team currently considers the following asset classes:

US Stocks represent an ownership share in US-based corporations. The US has the largest economy and stock market in the world. Although the US economy was hit hard in the 2008-2009 Financial Crisis, it is still one of the most resilient and active in the world because it is powered by a remarkable innovation engine.

Foreign Developed Market Stocks represent an ownership share in companies headquartered in developed economies like Europe, Australia, and Japan. Although the economies of Europe and Japan have experienced some struggles in the last few decades, Foreign Developed Markets represent a significant part of the world economy and provide diversification from US Stocks.

Emerging Market Stocks represent an ownership share in foreign companies in developing economies such as Brazil, China, India, South Africa, and Taiwan. Compared with developed countries, developing countries have younger demographics, expanding middle classes and faster economic growth. They account for half of world GDP, and that portion is likely to increase as the Emerging Markets develop. Emerging Market Stocks are more volatile, but we expect them to deliver higher returns than US Stocks and Foreign Developed Markets Stocks for the long term.

Dividend Growth Stocks represent an ownership share in US companies that have increased their dividend payout each year for the last ten or more consecutive years. They tend to be large-cap well-run companies in less cyclical industries and thus are less volatile than stocks more generally. Many companies in this asset class have higher dividend yields than their corporate bond yields and the yields on US government bonds.

US Bonds are high-quality debt issued by the US Treasury, government agencies, and US corporations. US Bonds provide steady income, low historical volatility and low correlation with stocks. Due to the low interest rate policy currently administered by the Federal Reserve, US bonds offer historically low yields and are expected to produce relatively low real returns.

US Corporate Bonds are debt issued by US corporations with investment-grade credit ratings to fund business activities. Compared to US Bonds, which contain large amounts of bonds issued by the US government and government agencies, corporate bonds offer higher yields due to higher credit risk, illiquidity, and callability.

Emerging Market Bonds are debt issued by governments and quasi-government organizations from emerging market countries. They offer higher yields than developed market bonds. Emerging Market Bonds had serial defaults in the 1980s, 1990s, and even 2000s. However, the world has changed. Emerging market countries with younger demographics, stronger economic growth, healthier balance sheets, and lower debt-to-GDP ratios, have less risk than most investors realize.

Municipal Bonds are debt issued by US state and local governments. Unlike most other bonds, Municipal Bonds' interest is exempt from federal income taxes. They provide individual investors in high tax brackets a tax efficient way to obtain income, low historical volatility, and diversification.

Treasury Inflation-Protected Securities (TIPS) are inflation-indexed bonds issued by the US federal government. Unlike nominal bonds, TIPS' principal and coupons are adjusted periodically based on the Consumer Price Index (CPI). Although TIPS currently have historically low yields, their inflation-indexed feature and low historical volatility makes them the only asset class that can provide income generation and inflation protection to risk averse investors.

Real Estate is accessed through publicly traded US real estate investment trusts (REITs) that own commercial properties, apartment complexes and retail space. They pay out their rents as dividends to investors. REITs provide income, inflation protection, and diversification benefits.

Commodities reflect the prices of energy (e.g., natural gas and crude oil). Commodities provide inflation protection and diversification. Investing in Commodities via exchange-traded products is also relatively tax efficient due to the favorable tax treatment on long-term capital gains and stock dividends.

There is no definitive answer to the question “how many asset classes should investors hold?” It is relatively easy to improve the risk-return tradeoff of a two- or three- asset class portfolio. It gets increasingly difficult to improve the returns of a portfolio already diversified across seven or eight asset classes. Going beyond a certain level of complexity generally reaches diminishing returns, especially when you incorporate ETF costs into your decision-making. Having said that, we will continue to evaluate new relatively uncorrelated asset classes that can be implemented using low-cost liquid ETFs, to improve our asset allocation.

Once we decide on our asset classes, our next step is to select the investment vehicles.

Selecting Investment Vehicles

Quantum Ai Trading uses low cost, index-based exchange traded funds (ETFs) to represent each asset class. In contrast, many financial advisors have historically recommended actively managed mutual funds. A significant amount of research has been published that shows active mutual funds not only underperform the market (Bogle, 2009; Malkiel, 2012), but those that outperform in one period are unlikely to outperform in subsequent periods (i.e. their returns are due to luck). In fact, the semi-annual review of active funds published by S&P Dow Jones Indices published in mid-2020 (SPIVA US Scorecard), indicates that between 67%-99% of active funds have underperformed their benchmarks over the last 15 years. As a result, index funds and, more specifically, passive index ETFs have exploded over the past 10 years. More than 2,000 ETFs have been created and in aggregate, ETFs have accumulated assets of more than $4 trillion (ICI 2020 Fact Book). Simultaneously, flows out of active mutual funds have accelerated dramatically.

Table 1 illustrates the average asset-weighted expense ratios of active mutual funds, and Quantum Ai Trading ETFs. Aggregate industry statistics for actively managed mutual funds are from Exhibit 2 of Morningstar (2020), and are as of the end of 2019. Data for Quantum Ai Trading reflect the expense ratios of the target asset allocations for taxable and retirement accounts weighted by the amount of client assets in each target allocation. The table illustrates the annual savings available simply from avoiding actively managed mutual funds. Put differently, a young investor who invests using active mutual funds would lose 17% of her investment to fund expense ratios over a 30-year investment horizon, more than seven and a half times as much as if she had invested through Quantum Ai Trading .

Quantum Ai Trading periodically reviews the entire population of ETFs to identify the most appropriate ones for use in our portfolio construction. When choosing ETFs, we consider the following criteria:

Cost: All things being equal, we attempt to choose the ETFs with the lowest expense ratios. Unfortunately, all things are not equal so we have to trade off cost for the other three characteristics.

Tracking error: Most investors are surprised to learn that ETFs do not exactly track the indices they were created to mimic. The higher the variance from its selected benchmark (tracking error), the less appropriate an ETF is to represent its asset class. An ETF issuer can reduce its tracking error by improving its operational systems, but that adds expense which is typically passed on as a higher management fee to the investor. In other words, expense and tracking error are often inversely correlated.

Liquidity: We choose ETFs that are expected to have sufficient liquidity to allow purchases and sales at any time. Newly issued ETFs usually take a while before they are appropriate for recommendation, even if they offer lower fees because the lack of liquidity may cause trading costs that more than offset their lower fees.

Securities lending: ETF issuers generate income from lending out their underlying securities to hedge funds to enable short sales; the more prevalent the lending, the higher the risk to the ETF buyer. We prefer ETFs that either minimize lending or share the lending revenue with their investors to lower management fees.

Allocating Assets

Quantum Ai Trading determines the optimal mix of our chosen asset classes by using Mean-Variance Optimization (Markowitz, 1952), the foundation of Modern Portfolio Theory. The output of the optimization is a collection of portfolios that generate the maximum return at each level of targeted risk, or equivalently, minimize the level of risk for a specific expected return. Collectively these portfolios form the (mean-variance) efficient frontier.

Mean-Variance Optimization

The expected return of the portfolio is a weighted average of the expected returns of the individual asset classes, μ, with the weights given by the portfolio allocations, w. The variance of the portfolio depends on the variances of the individual asset classes, but also on how they move with one another, collectively captured by the asset class covariance matrix, Σ. To identify mean-variance efficient portfolios we solve the following optimization problem:

Maximize: $\mu' \cdot w$

Subject to: $w' \cdot \Sigma \cdot w = \sigma^2$

$w \geqslant 0$

$w' \cdot \mathbb{1} = 1$

$w \in W$

Where:

μ denotes the asset class expected returns

w denotes the asset class weights, which are being optimized

Σ denotes the asset class covariance matrix

$\mathbb{1}$ is a vector of ones

σ is the target portfolio volatility. The expression $w' \cdot \Sigma \cdot w$ gives the expected annualized variance of the portfolio. The square root of this value is the annual volatility.

W represents a set of portfolios defined by extra constraints on the weights. "$w \in W$" means that the portfolio w must satisfy these constraints. The extra constraints include lower and upper bounds on the individual asset weights, and constraints of the weights of certain pairs of assets relative to each other.

Solving this problem for different values of the target volatility, σ, gives us a collection of portfolios that maximize expected return for each level of risk, and have weights that sum to one (i.e. a portfolio that is fully invested and does not use leverage), and, satisfy the lower- and upper-bound constraints on the weights. These constraints ensure that resulting portfolios are long-only (i.e. weights are positive) and are not overly concentrated in a small number of asset classes. Clients are recommended a portfolio based on the results of a risk questionnaire, which evaluates their ability and willingness to take risk.

Capital Market Assumptions

Mean-variance optimization (MVO) requires, as inputs, estimates of each asset class's expected return, volatility (standard deviation), and the pairwise correlations between asset classes. MVO is sensitive to input parameters and tends to produce concentrated and unintuitive portfolios if the parameters are naively specified. To overcome the difficulty of applying MVO in practice, Fischer Black and Robert Litterman proposed the Black-Litterman model while working at Goldman Sachs (Black & Litterman, 1992). Their model applies a technique that derives expected return parameters from equilibrium allocations and manager views. It largely mitigates the optimizer's sensitivity problem and enables it to produce diversified and intuitive portfolios. In addition, the Black-Litterman model provides a flexible framework to express views about asset class returns, which ultimately will be reflected in the asset allocation. In this section, we describe how we generate our capital market assumptions and how we use the Black-Litterman framework to identify optimal portfolios.

Expected Returns

To construct estimates of each asset class's expected return we use the Black-Litterman model to blend expected returns from the Capital Asset Pricing Model (CAPM) (Sharpe, 1964), computed based on the composition of the global market portfolio, with long-term expectations obtained from the Quantum Ai Trading Capital Markets Model.

The CAPM is a simple, one-factor model which predicts that the expected return of each asset class is proportional to its beta relative to the market portfolio. The CAPM was recognized with a Nobel Prize in 1990, and remains the cornerstone of modern finance models. Professors Eugene Fama and Kenneth French (1992, 1993) demonstrated that the CAPM provides an incomplete description of expected returns across different types of stocks (e.g. small vs. Large, value vs. Growth), as well as across asset classes, which led to the introduction of multi-factor models. The work of Eugene Fama around market efficiency and multi-factor models was itself recognized with a Nobel Prize in 2013. Building on these insights, we developed the Quantum Ai Trading Capital Markets Model (WFCMM), which is a multi-factor model with risk premia that can vary over time based on changes in interest rates and valuation ratios. We use the WFCMM to generate forecasts of long-horizon expected returns, which we blend with the predictions of the CAPM using the Black-Litterman model.

The Black-Litterman approach to constructing expected return requires three steps (Walters, 2014). First, the composition of the global market portfolio is used in a "reverse optimization" step to obtain the market-implied expected returns for each asset class. Effectively, this step identifies what asset class expected returns would have to be in order to make the observed market portfolio the optimal portfolio for a representative investor. Second, these market-implied expected returns are blended with views using a Bayesian approach, which ensures that: (a) the weights assigned to the two sets of views reflect their relative precisions; and, (b) the views are distributed across the asset classes in an internally consistent manner. In our case, the "views" are the forecasts of expected returns obtained from the multi-factor Quantum Ai Trading Capital Markets Model (WFCMM).

These blended values constitute the pre-fee, pre-tax estimate of each asset class's expected return. From this gross return, we subtract the expenses of the ideal instrument that could be used to represent each asset class to get the net-of-fee expected return. A list of each asset class's net-of-fee pre-tax returns is presented in Table 2.

To calculate the optimal asset allocation for taxable and tax-deferred (retirement) accounts, we need to determine each asset class's net-of-fee, after-tax return. The taxation of investment returns depends on their composition (income vs. Capital gains), and the type of account they are held in (taxable vs. Retirement). In a taxable account, income distributions (dividends and interest) are subject to taxation at ordinary income rates, and are taxed at the time of the distribution. There are a few important exceptions to this. First, some dividends, known as "qualified dividends," are taxed at the lower, long-term capital gains rates. Second, interest on municipal bonds is exempt from taxation at the federal level, and potentially the state level (e.g. if the bonds are issued by the state you are a resident of). Unlike in a taxable account, where only the net-of-tax portion of the distribution can accumulate over time, in a retirement account, income distributions are not taxed at the time they happen, which allows your money to accumulate in a tax-deferred fashion.

Finally, the two account types differ in the taxation of the accumulated capital gains. In a taxable account, even in the absence of add-on deposits, the cost basis of your investments increases over time as the net-of-tax amount of the income distribution is reinvested. When you withdraw your assets, the gain relative to this cost basis is taxed at long-term capital gains rates (assuming you have held the investment for at least a year). In a traditional retirement account, you pay income tax on the entire withdrawal amount — contributions plus appreciation — at ordinary income rates, since the investments were made with pre-tax dollars. In a Roth retirement account, no taxes are due on withdrawals, since the investment was made with after-tax dollars (i.e. you already paid income tax on the amount invested). The principal difference between these two retirement accounts types is whether you pay ordinary income tax today or in the future.

To estimate how much of the pre-tax expected return is likely to be lost to taxes (i.e. tax drag) on an annualized basis, we need to determine:

For each asset class, the fraction of the expected return that will be distributed each year, either in the form of ordinary income (dividends, interest, short-term capital gains) or long-term capital gain.

For each asset class, the fraction of dividend distributions that will be treated as qualified, and thus subject to taxation at long-term capital gains rates.

For each account type, the projected time until liquidation, which is necessary to amortize the taxes due at liquidation (capital gains in taxable accounts, and ordinary income in traditional retirement accounts) over the life of the investment.

For each asset class, we estimate the fraction of the total return that will be distributed each year based on a combination of historical and projected data (e.g. interest rates, dividend yields). The fraction of distributions subject to qualified dividend treatment is estimated based on historical data. We assume a combined ordinary income tax rate of 30.4% (24% federal + 6.4% state), applicable to Quantum Ai Trading ’s median client weighted by assets. The household is subject to a 15% federal long-term capital gains rate and a 24% federal short-term capital gains rate. Although these assumptions are only true for our median client, we find that the portfolios generated by our process are fairly insensitive to them. Finally, we assume that investments in the taxable account will be liquidated in 10 years, whereas those in the retirement account will be liquidated in 30 years. The majority of Quantum Ai Trading ’s clients are under 45 years of age, and have a relatively long horizon until they begin drawing on their retirement accounts. We use a shorter horizon for taxable accounts as clients may use those assets for nearer-term goals, such as a home purchase or educational expenses. The applicable tax rates and the household’s income tax bracket are assumed to remain unchanged over this period.

Using Monte Carlo, we simulate the pre-tax returns of each asset class, apply the relevant tax rules within the two account types, and then compute the net-of-fee, after-tax return. This methodology allows us to assess the combined impact of taxes on the intermediate distributions, as well as the liquidation of the account. The difference between the annualized pre-tax and after-tax rates captures the tax drag, i.e. the amount lost to taxes annually. Table 3 reports the tax drag and net-of-fee, after-tax rates of return for each asset class when held in taxable and retirement accounts.

We use these net-of-fee, after-tax rates of return as inputs to the mean-variance optimization to determine the efficient frontier. The estimates change over time as we incorporate new market data into our models, and we periodically release new asset allocations based on our latest data and portfolio construction methodology. Because the adoption of a new allocation may result in tax consequences from realized gains, we will not transition clients to a new allocation without offering an opportunity to choose to stay on their existing one.

It is important to note that we did not consider the benefits from Tax-Loss Harvesting when assessing expected returns for taxable accounts. Asset classes differ in their volatilities and thus their tax-loss harvesting potential, which would change their after-tax expected returns.

Variance-Covariance Matrix

To derive an estimate of the asset class covariance matrix, we rely on historical data, combined with factor analysis and shrinkage. As is now well understood, simple sample-based covariance matrix estimates tend to be unstable, and result in extreme allocations when applied in a portfolio selection context. Shrinkage is a statistical approach that has evolved to address this instability by shrinking the empirical estimator toward a pre-specific target (Ledoit and Wolf, 2004). Specifically, we shrink the estimate of the idiosyncratic component of the asset class covariance matrix toward a diagonal matrix, consistent with the theoretical prediction of the factor model.

Using a long time series of monthly return data, we first estimate the loadings (“betas”) of each asset class onto a collection of risk factors, capturing common sources of variation in realized returns. Stacking the betas of the N asset classes onto the K risk factors into a single matrix gives us an N x K matrix, B. We then estimate an N x N covariance matrix of factor regression residuals, Σ_i, capturing the non-systematic or idiosyncratic risk of each asset class. Finally, we compute the K x K covariance matrix of historical factor returns, Σ_f. This provides us with a factor-based decomposition of the historical asset class return covariance matrix, Σ.

This approach effectively partitions the risk of each asset class into a systematic component, $B \cdot \Sigma_f \cdot B'$, which investors are compensated for bearing, and an idiosyncratic component, Σ_i, which is uncompensated. If the chosen set of factors perfectly described the economic dynamics of the set of assets, the idiosyncratic covariance matrix would be diagonal (i.e. all of the comovement would have been captured through the factor exposures). Although this will not be the case in any historical sample, due to sample-specific variation and the potential for model misspecification, a diagonal idiosyncratic covariance matrix provides a sensible, theoretically-motivated shrinkage target. We denote the shrunken idiosyncratic covariance matrix, . Finally, we combine the shrunken idiosyncratic covariance matrix estimator, with the systematic component, to obtain the estimator of the asset class covariance matrix:

From we can compute the volatilities of the individual asset classes, and the correlation matrix of the asset class returns. These results are reported in Tables 4 and 5, respectively.

The volatility estimates confirm that stocks are generally riskier than bonds, Foreign Stocks are generally riskier than US Stocks, and that, even within an asset class there can be considerable variation in risk (e.g. US Bonds vs. US Corporate Bonds vs. Emerging Market Bonds). Finally, investments focused on a smaller subset of assets (e.g. Real Estate and Commodities) tend to be less diversified and have higher volatility.

The correlations between US stocks and US bonds are close to zero, showing that bonds have been a very good diversifier for equity investments. Correlations between different types of stocks have increased recently reflecting greater global integration across economies and capital markets. Similarly, Real Estate and Commodities are more correlated with broad equity indices today than in the 1980s and 1990s. Across different types of bonds, correlations with equities range from zero (US Government Bonds), to slightly positive (US corporate bonds), and very positive (Emerging Market Bonds). This trend reflects the increasing credit risk of these different types of bonds.

Portfolio Construction

We use the estimates from the variance-covariance matrix of asset class returns, and the net-of-fee, after-tax expected returns for each asset class as inputs to the mean-variance optimization to determine the optimal portfolio for each level of risk. Additionally, we enforce minimum and maximum allocation constraints for each asset class that are displayed in Table 6. The minimum allocation constraints are set at zero in order to ensure that the optimized portfolios are long-only (i.e. do not involve any short positions). We selected 35% as the maximum allocation for most asset classes to ensure sufficient diversification. Other respected sources (including Swensen, 2005) recommend similar maximum asset class allocations. US Stocks are an exception, with a maximum allocation at 45%. US Stocks represent a significant proportion of the world's stocks and make up roughly 57% of the MSCI All-Country World Index (ACWI)* as of May 2021. Another exception to the 35% maximum is Emerging Market Bonds, which have a high expense ratio and are relatively tax-inefficient. We find excluding Emerging Markets Bonds from taxable allocations and limiting their total weight to 10% in IRA allocations results in good tradeoffs between after-tax return and overall expense ratio. We exclude REITs from taxable portfolios, as tax forms distributed by REIT ETFs are commonly restated or distributed late, complicating tax filings for investors.

- **MSCI ACWI FactSheet (May 2021)**

Taxable and Retirement Account Allocations

We construct two sets of portfolio allocations: one for taxable accounts, and one for retirement accounts. Each set of portfolio allocations contains twenty portfolios with varying levels of portfolio volatility. We define the lowest volatility allocation to have a Risk Score of 0.5 and the highest a Risk Score of 10.

Figure 1 presents the optimal allocations for taxable accounts. Depending on the targeted level of risk, the portfolios contain between five and eight asset classes including US Stocks, Foreign Developed Stocks, Emerging Market Stocks, Dividend Growth Stocks, US Bonds, US Corporate Bonds, Municipal Bonds, and TIPS. As the risk level increases from left to right, the allocation to lower risk/lower return asset classes such as TIPS and Municipal Bonds decreases, while the allocation to higher risk/higher return asset classes such as US Stocks, Foreign Developed Stocks, and Emerging Market Stocks increases. Municipal Bonds emerge as the primary bond asset class in the allocation because they have higher net-of-fee, after-tax expected returns due to their federal tax exemption. Emerging Market Bonds are excluded due to their relatively high expense ratio.. Equities not only offer higher returns, but are more tax efficient, since their dividends are taxed at qualified dividend rates, which are less than the ordinary income tax rates that are applied to bond interest.

Figure 2 presents the optimal asset allocations for retirement accounts. The allocations include eight unique asset classes, with five to eight applied to any one portfolio. As the risk level increases from left to right, allocation to conservative asset classes such as US Bonds and Corporate Bonds decreases, while allocation to aggressive asset classes such as US Stocks, Foreign Developed Stocks, Emerging Market Stocks, and Real Estate increases. Emerging Market Bonds behave somewhere between conservative and aggressive asset classes. Dividend Growth Stocks are allocated only in the conservative portfolios for risk-averse investors, while risk-tolerant investors have larger allocations to broad-market stocks and Real Estate for inflation protection. Commodities are not used because they don't add economic benefit (i.e. increased return for the same risk) in the presence of the other asset classes.

Handling Small Accounts

Quantum Ai Trading accounts can be as small at $100, which doesn't always provide sufficient cash for meaningful exposure to all of the asset classes we recommend. As a result, for such small accounts, we use a process of holistic optimization to select the available investment ETFs that best match the expected performance of the desired portfolio allocation while minimizing the "cash drag" from any uninvested assets. Our backtesting shows that this optimization process typically results in portfolios with a smaller number of asset classes, minimal cash drag, and a strong match for the historical performance of the desired target portfolio. What's more, as these accounts grow in size they gracefully evolve into our typical portfolio allocations.

Determining Risk Tolerance

Once the Efficient Frontier has been established, it is necessary to pinpoint an investor's risk tolerance in order to identify the ideal asset allocation for her needs. Rather than asking the typical 25 questions asked by financial advisors to identify an individual's risk tolerance, Quantum Ai Trading combed behavioral economics research to simplify our risk identification process to only a few questions. For example, we are able to project an individual's income growth and saving rate based on their age and current income. We ask prospective clients questions to evaluate both their objective capacity to take risk and subjective willingness to take risk. Our view is that sophisticated algorithms can do a better job of evaluating risk than the average traditional advisor.

We ask subjective risk questions to determine both the level of risk an individual is willing to take and the consistency among her answers. The less consistent the answers, the exponentially less risk-tolerant the investor is likely to be. For example, if an individual is willing to take a lot of risk in one case and very little in another, then she is inconsistent and is therefore assigned a lower Risk Score than the simple weighted average of her answers.

We ask objective risk questions to estimate with as few questions as possible whether the individual is likely to have enough money saved at retirement to afford her likely spending needs. The greater the excess income, the more risk the customer is able to take. Conversely, if her expected retirement income is less than her likely retirement spending needs, then she cannot afford to take much risk with her investments.

Our overall Risk Score combines subjective and objective risk tolerance, with a heavier weighting to whichever component is more risk averse. We chose this approach because behavioral economics research shows individuals consistently overstate their true risk tolerance, especially male investors who are educated and overconfident (Barber & Odean, 2001). Relying on an investor's biased answers may lead to a more volatile portfolio than appropriate, which could increase the likelihood the investor sells when the market declines. DALBAR published a study that observed the average equity mutual fund investor underperformed the S&P 500 by 4.92% on an annualized basis during the 30-year period 1998-2019 due to consistently buying after the market has risen and selling when the market declines (DALBAR, 2020).

The composite Risk Scores range from 0.5 (most risk averse) to 10.0 (most risk tolerant) in 0.5 increments. In turn, each Risk Score corresponds to one of the twenty asset allocations described in the previous section.

We email our clients periodically to determine if anything in their financial profile has changed that may affect their risk tolerance. For example, getting married, having kids, benefiting from equity appreciation associated with an IPO or being promoted to a significantly higher paying job can have a major impact on the Risk Score we apply and therefore one's ideal investment mix.

We inform our customers about the impacts of changing their Risk Score frequently, and that it might not be appropriate for their ultimate goals. This is because we believe attempting to time the market is one of the most serious mistakes investors can make, and changing Risk Scores frequently should not be used as a tool to try to time the market. We recommend that clients review their Risk Score annually and only consider updating it every three years or so, or if they experience a significant change in financial circumstances.

Rebalancing and Ongoing Monitoring

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 in our experience: (1) portfolio risk increases as higher-risk portions of the portfolio grow beyond their original allocations, and (2) allocations become sub-optimally mixed. To maintain the intended risk level and asset allocations, a portfolio must be periodically rebalanced. Sophisticated algorithms are required to optimize rebalancing subject to tax and trading expense effects.

Quantum Ai Trading monitors our clients' portfolios and periodically rebalances each portfolio when dividends from ETFs accrue, a deposit or withdrawal has been made, or if movements in their relative allocations justify a change. Our rebalancing algorithms trade off deviations from the target portfolio with the tax consequences of selling appreciated assets. We use cash inflows to buy underweight asset classes and threshold-based rebalancing instead of time-based rebalancing in an effort to reduce turnover, taxes, and trading costs. Rebalancing will usually reduce risk over time, but not necessarily increase returns.

It is important to note that a client's asset allocation will typically need to be adjusted over time as his/her investment goals and risk tolerance may change. Quantum Ai Trading recommends our clients review their investment plans in detail every three to five years to determine whether their risk tolerance and target allocation should be updated. We also remind our clients on a quarterly basis to keep us informed of any such changes.

Conclusion

Quantum Ai Trading combines the judgment of its investment team with state of the art optimization tools to identify efficient portfolios. We strive to deliver the maximum net-of-fee, after-tax, real investment return for each client's particular tolerance for risk. This means we will continue to look for meaningful ways to improve our investment methodology in the future while continuously monitoring and periodically rebalancing our clients' portfolios to maximize returns while maintaining their calculated risk tolerance. We believe following this process will lead to outstanding long-term financial outcomes for our clients.

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To capture the historical performance of asset classes, we used historical return data for instruments tracking the following indices: US Stocks (CRSP US Total Market Index), Foreign Developed Stocks (MSCI EAFE Index), Emerging Market Stocks (MSCI Emerging Markets Index), Dividend Stocks (Dow Jones US Dividend 100 Index), US Govt Bonds (Barclays US Aggregate Bond Index), US Corporate Bonds (iBoxx Liquid

Investment Grade Index), Emerging Market Bonds (JPMorgan EMBI Global Core Index), Municipal Bonds (S&P Municipal Bond Index), TIPS (Barclays US Inflation-linked Bond Index), Real Estate (FTSE NA REIT US Real Estate Index), Commodities (S&P Energy Select Sector Index Index). The choices made by Quantum Ai Trading to use certain instruments may affect the performance calculations, and different choices would result in different performance estimates. Various strategies and assumptions may affect performance, such as ETF selection, ETF tracking error and expenses, and rebalancing of allocations.

To construct forward-looking projections of each asset class's expected returns, we combined forecasts from the Capital Asset Pricing Model (CAPM) with forecasts from a proprietary multi-factor model ("Views") using the Black-Litterman framework. The CAPM forecast is constructed on the basis of: (a) an estimate of the composition of the global market portfolio; (b) an estimate of the variance-covariance matrix of asset class returns estimated from monthly historical data; and, (c) an assumed parameter measuring the risk tolerance of an average investor. To construct views we combine estimates of each asset class's exposure to a collection of economic risk factors (obtained using historical return data) with projections of the forward looking risk-free rates and risk premia (obtained via Monte Carlo simulation of the Quantum Ai Trading Capital Markets Model).

The projections and other information generated by the Quantum Ai Trading Capital Markets Model (WFCMM) are hypothetical in nature, do not reflect actual investment results, and are not guarantees of future results. WFCMM results will vary with each use and over time. The WFCMM projections are based on a statistical analysis of historical data. Future returns may behave differently from the historical patterns captured in the WFCMM. More importantly, the WFCMM may be underestimating extreme negative scenarios unobserved in the historical period on which the model estimation is based.

The WFCMM is a proprietary financial simulation tool developed and maintained by Quantum Ai Trading 's Research group. The model forecasts distributions of future realization of economic risk factors, valuation ratios, and US Treasury yields. The theoretical and empirical foundation for the WFCMM is that the returns of various asset classes reflect the compensation investors require for the passage of time (risk-free rate) and for bearing different types of systematic risk (beta). At the core of the model are estimates of the dynamic statistical relationship between risk factors and asset returns, obtained from statistical analysis based on available monthly financial and economic data. Using a system of estimated equations, the model then applies a Monte Carlo simulation method to construct forward-looking forecasts. The model generates a large set of simulated outcomes for each asset class over several time horizons. Forecasts are obtained by computing measures of central tendency in these simulations. Results produced by the tool will vary with each use and over time.

The information in this document may contain projections or other forward-looking statements regarding future events, targets, forecasts or expectations that are based on Quantum Ai Trading 's current views and assumptions and involve known and unknown risks and uncertainties that could cause actual results, performance or events to differ materially from those expressed or implied in such statements. Neither the author nor Quantum Ai Trading or its affiliates assumes any duty to, nor undertakes to update forward looking statements. Actual results, performance or events may differ materially from those in such statements due to, without limitation, (1) general economic conditions, (2) performance of financial markets, (3) changes in laws and regulations and (4) changes in the policies of governments and/or regulatory authorities. Any opinions expressed herein reflect our judgment as of the date hereof and neither the author nor Quantum Ai Trading undertakes to advise you of any changes in the views expressed herein.

Hypothetical expected returns information have many inherent limitations, some of which, but not all, are described herein. No representation is being made that any client account will or is likely to achieve performance returns or losses similar to those shown herein. In fact, there are frequently sharp differences between hypothetical expected returns and the actual returns subsequently realized by any particular trading program. One of the limitations of hypothetical expected returns is that they are generally prepared with the benefit of hindsight. In addition, hypothetical trading does not involve financial risk, and no hypothetical trading record can completely account for the impact of financial risk in actual trading. For example, the ability to withstand losses or adhere to a particular trading program in spite of trading losses are material points which can adversely affect actual trading results. The hypothetical expected returns contained herein represent the application of the rule-based models as currently in effect on the date first written above and there can be no assurance that the models will remain the same in the future or that an application of the current models in the future will produce similar results because the relevant market and economic conditions that prevailed during the hypothetical performance period will not necessarily recur. There are numerous other factors related to the markets in general or to the implementation of any specific trading program which cannot be fully accounted for in the preparation of hypothetical performance results, all of which can adversely affect actual trading results. Hypothetical expected returns are presented for illustrative purposes only. No representation or warranty is made as to the reasonableness of the assumptions made or that all assumptions used in achieving the returns have been stated or fully considered. Changes in the assumptions may have a material impact on the hypothetical returns presented.

Correlation is a measure of statistical association, or dependence, between two random variables. The values presented here are based on a particular historical sample period, data frequency, and are specific to the assets/indices used in the analysis. Correlations may change over time, such that future values of correlation may significantly depart from those observed historically.

Past performance is no guarantee of future results, and any hypothetical returns, expected returns, or probability projections may not reflect actual future performance. Actual investors may experience different results from the expected or hypothetical returns shown. There is a potential for loss that is not reflected in the hypothetical information portrayed. The expected returns shown do not represent the results of actual trading using client assets but were achieved by means of the retroactive application of a model designed with the benefit of hindsight.

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