Optimal FOMO Portfolios
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Portfolio optimization routines typically assume that investors are focused entirely on the risk of their portfolios and are agnostic to the performance of specific assets, either within or outside the investable opportunity set. In reality, the performance of certain assets has the potential to affect the perceived efficacy of a portfolio ex post more than others. For example, the performance of the overall stock market, such as the S&P 500 for U.S. investors, is frequently covered in the financial media and the disutility from underperforming the market when it is doing well is likely going to be higher than underperforming when the market is doing poorly, i.e., there is clear asymmetry in outcomes.

Regret has the potential to affect investor decision-making, especially for households, which tend to be less sophisticated and are more likely to exhibit trend-chasing, i.e., making decisions based on the fear of missing out or FOMO. This article introduces an extension to the traditional portfolio optimization function to explicitly incorporate regret aversion. The approach effectively decomposes the return distribution of a portfolio into risk aversion, which is effectively downside risk, i.e., returns below some target return, such as 0 percent, and regret aversion, which involves comparing the performance of the portfolio to one or more regret benchmarks. We determine optimal portfolios by running a series of optimizations using historical stock returns.

Considering regret aversion materially can affect optimal portfolio weights, depending on investor preference and modeling assumptions. Interestingly, allocations to assets may increase as they become increasingly inefficient, i.e., as volatility increases, in the presence of regret, given the role of positive skewness. This is intuitive in this model, to some extent; however, it is inconsistent with traditional portfolio optimization techniques, e.g., mean-variance optimization, where asset weights decline as they become increasingly inefficient.

The objective of this research is not to suggest that financial advisors or asset managers should start allocating to inefficient assets because some clients may experience regret, but rather to provide a model for building portfolios in light of regret aversion and to provide a better way to address the notion of regret within a total portfolio construct.

Regret is not something that is typically explicitly considered when building a portfolio despite its potential implications on the ex post perceived of an investment outcome. This article introduces an approach to incorporate regret aversion into portfolio optimizations as a distinct parameter from risk aversion and explores the implications of regret on a multi-asset portfolio. The analysis suggests that incorporating regret aversion can materially affect optimal portfolio weights, depending on investor preference and modeling assumptions, and that regret likely should be more thoughtfully considered when developing portfolios for clients.

WHAT MIGHT HAVE BEEN
There are decades of research on the implications of regret in general household decision-making, as well as its role in investing. Most research on regret is rooted in psychology, because regret is described primarily as an emotional response to a decision, in particular comparing the outcome of a given decision to other potential opportunities.

Regret in investing can be linked to the emotional asymmetry that can occur based on different realized outcomes. For example, the performance of U.S. large-cap stocks, e.g., the S&P 500, is more salient for U.S. investors than non-U.S. large-cap stocks, e.g., the MSCI EAFE, given significant coverage of the U.S. markets in the U.S. media. Therefore, the potential regret, i.e., disutility, a U.S. investor would experience from missing out on strong U.S. stock performance is likely significantly higher than what that same investor would experience from missing out on non-U.S. stock performance. This
concept could at least partially explain the home-bias effect that exists within global equity markets.\(^1\)

Regret does not necessarily have the same financial implications on outcomes as downside risk, i.e., it’s just not making money versus losing money. However, that doesn’t mean it should be ignored, especially if ignoring regret increases the probability of an investor abandoning a diversified, professionally managed portfolio and placing a significant overweight on some type of volatile asset beyond what would even be considered rational for the investor’s preferences.

The notion of regret is especially important for households, which are prone to trend-chasing. This concept is likely best characterized colloquially in the concept of FOMO. In scientific literature, the term FOMO generally is defined as the apprehension that others are having rewarding experiences from which one is absent and the persistent desire to stay connected with people in one’s social network. The first aspect is related to cognitive anxiety, e.g., worry, rumination, etc., and the latter component involves a behavioral strategy aimed at relieving such anxiety. The way households receive information about investments has changed recently, especially given the rise of social media platforms, making FOMO an increasing threat to investors with respect to maintaining a diversified portfolio.

Introducing the notion of regret into a portfolio optimization routine is at least an implicit acknowledgment that investors are not simply utility-maximizing robots. Building portfolios consistent with this concept is rooted in research on behavioral portfolio theory, which considers security, the need for potential, an aspiration level, the strength of fear versus hope, and the strength of the desire to reach the aspiration level, among other factors.

Regret could manifest itself in a variety of ways for retail investors, especially for relatively risky assets that appear prominently in the media.\(^2\) Although avoiding allocation to risky, inefficient assets may appear to be the most obvious solution, to the extent the asset subsequently does well and the investor subsequently abandons the diversified portfolio and significantly overweight the asset could put future financial goals in peril. We’ve witnessed this effect numerous times throughout history and around the world, with tulips in the 1630s, tech stocks in the late 1990s, real estate before the Great Financial Crisis, and even cryptocurrencies.

**INTEGRATING REGRET INTO PORTFOLIOS**

A mean–variance investor’s preferences can be expressed using equation 1, where the goal is to maximize utility (\(U\)) based on the expected return of the portfolio (\(r_p\)), the investor’s risk aversion (\(\lambda\)), and expected variance of the portfolio (\(\sigma_p^2\)) by changing weights to the opportunity set of investments or assets.\(^3\)

\[ U = r_p - \lambda \sigma_p^2 \]  

(1)

Because risk in equation 1 is defined as the portfolio’s variance, it would include the entire distribution of returns. This is a reasonable approach to capturing risk if returns are normally distributed but likely would be suboptimal if returns were not normally distributed, especially by design, e.g., strategies that employ financial options.

For our model, as introduced in Blanchett (2023), the portfolio return distribution is decomposed to effectively separate target risk, i.e., return variability, and regret. Risk is defined as downside deviation, which targets the left part of the return distribution, but regret is estimated using a relative downside metric focused effectively on the right part of the distribution, or, more distinctly, returns below the regret benchmarks.

More formally, risk aversion is estimated by comparing the return of the portfolio (\(r_p\)) against a specific return target (\(r_T\)) given some risk aversion level (\(\lambda_{Risk}\)). In this model, only returns below a target are considered as contributing to the risk of the portfolio. The return target could be some minimally acceptable return required to achieve a goal, or, more simply, 0 percent, i.e., where risk is assumed to be negative returns.

The regret aversion metric compares the return of the portfolio to one or more regret benchmarks (\(RB\), where each regret benchmark would have its own specific regret aversion coefficient (\(\lambda_{Regret, RB}\)). Although only two regret benchmarks are included in equation 2, the model easily could be expanded to consider an infinite number of regret benchmarks, including those that are not necessarily in the investable opportunity set. It could make sense to include certain thresholds when considering regret aversion, for example, only those instances where the regret benchmark outperforms the portfolio by some level, e.g., 20 percent, or only when the returns fall within some range; however, for this analysis we focus on the entire distribution.

If returns are assumed to be normally distributed and the investor had no regret benchmarks, the optimal portfolio allocations using equations 1 and 2 should be very similar, if not identical, depending on the specific assumptions.

\[ U = r_p - \left[ \lambda_{Risk} \sqrt{\text{max}(0, r_p - r_T)} \right] + \lambda_{Regret, RB1} \sqrt{\text{max}(0, r_p - r_{RB1})} + \lambda_{Regret, RB2} \sqrt{\text{max}(0, r_p - r_{RB2})} + \ldots \]  

(2)

Assigning a risk aversion coefficient (\(\lambda_{Risk}\)) and a regret aversion coefficient (\(\lambda_{Regret}\)) for an investor is obviously a somewhat ambiguous exercise, especially because the risk and regret values are combined; however, higher values for each clearly would be associated with higher aversion levels.

For our analysis, we generate multivariate normal return distributions\(^4\)
classes, which is intentional. Although certain asset classes are going to be slightly more efficient than others, especially within a total portfolio context when correlations are considered, 5 most forward-looking capital market assumptions assume a relatively linear relationship (ex ante) between risk and return with a given opportunity set.

There are two obvious exceptions to the general linear relationship in figure 1, the inefficient asset and the volatile asset. The inefficient asset represents the average attributes of the four equity asset classes, i.e., risk and correlations, but it has a 100-basis-point lower expected average return. The volatile asset is especially inefficient, with a 0-percent return and 30-percent standard deviation (but with a zero correlation) and is included to reflect an asset that has especially unattractive basic attributes but may warrant an allocation depending on the regret preferences of the investor.

When solving equation 2 for our analysis, the geometric return during the 100-year period is used for portfolio return \( r_p \) versus the arithmetic return because the geometric return reflects the expected long-term return the investor will achieve from owning the portfolio, i.e., it incorporates the impact of volatility drag. We explore various optimization results in the next section.

PORTFOLIO ALLOCATION RESULTS

Figure 2 provides context around the optimal asset class weights for an investor with no assumed regret aversion that includes all nine assets under consideration. These results therefore provide the reader with context about how the portfolio risk levels and asset class weights evolve for different risk aversion coefficients, which range from 0.1 to 2.0 in 0.1 increments.

Using these assumptions, an investor with a risk aversion coefficient of 0.1, i.e., a highly risk-tolerant investor, would invest in a risky portfolio for a set of seven general investment asset classes: cash, U.S. bonds, non-U.S. bonds, U.S. large-cap equities, U.S. small-cap equities, non-U.S. equities, and emerging market equities, as well as two additional investments, which we call an inefficient asset and a volatile asset. For each set of preferences, we solve 50 trials with each consisting of 100 years of returns. A resampling approach is used to incorporate the fundamental uncertainty, i.e., estimation error, associated with forecasting future market conditions. The optimal portfolio weights are defined as the average asset class weights to the opportunity set across the 50 trials, although more complex approaches could be considered.

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The weights across asset classes remain relatively consistent. Figure 3A shows the corresponding allocations to the asset classes when considering only risk aversion. Figure 3B shows the resulting allocations to the asset classes when considering risk aversion and regret aversion.

As expected, the allocations to assets increase considerably when a regret aversion coefficient is included in the optimizations. This has important implications when considering regret aversion. As expected, the allocations to assets increase considerably when a regret aversion coefficient is included in the optimizations. This has important implications when considering regret aversion.

The relative weights across allocations do not shift that much when introducing a regret aversion coefficient; however, the inclusion of the regret aversion coefficient does increase allocations to risky assets, which are defined as all predominantly in emerging markets equities (44.3 percent), non-U.S. equities (39.2 percent), and U.S. small-cap equities (10.3 percent). As risk aversion increases, allocations to these assets decline and allocations to U.S. bonds and especially cash start to increase.

The inefficiency asset and volatile asset receive relatively de minimis allocations, averaging only 0.6 percent and 2.0 percent across all risk aversion levels, respectively. Weights for each are highest at the more moderate risk aversion levels. For example, the weights are 1.2 percent and 2.6 percent for the two assets, respectively, when the risk aversion coefficient is 0.9. Note, the equity allocation for the optimal portfolios, where the opportunity set includes only the seven normal investment asset classes, assuming a risk aversion coefficient of 0.9, is 42.0 percent, so the risk aversion level generally would be described as moderately risk averse.

The fact that the inefficient asset or the volatile asset receives an allocation can be attributed to the resampling approach used to determine the optimal portfolios. Although the assets are relatively inefficient, on average, they do relatively well in certain trials, which results in the allocation. The fact that the volatile asset receives a higher allocation, even though it is more inefficient, can be attributed to its higher volatility. This has important implications when considering regret aversion.

Next, we conduct a series of optimizations for the same range of risk aversion coefficients (0.1 to 2.0, in 0.1 increments, inclusive), but we include a regret benchmark and corresponding regret aversion level. We do so for three separate regret benchmarks: U.S. large-cap equities, the inefficient asset, and the volatile asset. When running the optimizations for the U.S. large-cap equities we exclude the inefficient asset and the volatile asset from the opportunity set, and when running the optimizations for the inefficient asset and the volatile asset we exclude the asset without the regret aversion coefficient.

The fact that either the inefficient asset or the volatile asset receives an allocation can be attributed to the resampling approach used to determine the optimal portfolios. Although the assets are relatively inefficient, on average, they do relatively well in certain trials, which results in the allocation. The fact that
assets except cash, U.S. bonds, and non-U.S. bonds. Inclusion of the regret aversion coefficient also increases overall portfolio risk, which is defined as the average downside risk across trials. This effect is shown in figure 4.

In other words, the presence of regret aversion should result in higher allocations to riskier assets, on average, especially if the regret benchmark is relatively risky. The shift can be relatively extreme. For example, a risk aversion coefficient of 1.0 would be associated with a 36.0- percent allocation to risky assets without regret aversion, but the risky asset allocation increases to 59.7 percent assuming a 0.25 regret aversion coefficient with the inefficient asset.

Effectively the allocations to the assets that have a regret benchmark shift the base risk aversion results to the right. The portfolios with higher risk aversion levels still exhibit overall portfolio allocations that are dominated by cash and U.S. bonds but are simply riskier.

Allocating to less-efficient assets obviously will make a portfolio less efficient than when considering risk aversion alone, but the resulting level of inefficiency of the portfolio will depend on the expected inefficiency of the regret benchmarks. One interesting effect we noticed when running a variety of optimizations is that making assets with a regret aversion coefficient more inefficient can result in a higher potential allocation, which makes the portfolio increasingly inefficient, all other things being equal. For example, if we run a separate series of optimizations but vary the standard deviation of the volatile asset, its resulting allocations potentially can increase, on average, at higher assumed volatility levels, an effect illustrated in figure 5.

Making the volatile asset more inefficient, i.e., increasing the standard deviation, generally increases the allocations, especially at lower risk aversion levels, i.e., for more risk-tolerant investors. In other words, investors who experience higher levels of regret would have higher allocations to higher-volatility assets, although even then, there is clearly a limit. These findings are consistent with the research of Baule et al. (2019), who also note that investments with more skewness can be more attractive in optimization models that incorporate regret.

This finding has important implications for highly speculative investments, such as cryptocurrencies. Although interest in
cryptocurrencies has waned recently given the significant contraction in prices, at one point nearly one in six U.S. adults had invested in, traded, or used a cryptocurrency according to research by the Pew Institute.⁶

Although it is difficult or possibly impossible to generate forward-looking capital market assumptions on cryptocurrencies, generally they would be considered relatively risky. Investors who do not care about or follow the cryptocurrency or digital asset space likely would not experience regret aversion and therefore it generally would not make sense to include these assets in a portfolio. However, it may be sensible for an investor who is interested in digital assets, e.g., cryptocurrencies, to allocate a relatively small part of the portfolio to them to satiate potential regret if the asset does relatively well, i.e., hedge against the regret of the positive skew. Although allocating to cryptocurrencies (in this example, assuming the volatile asset is a reasonable proxy) would make the portfolio less efficient, it is effectively a compromise for those investors interested in owning the asset and still maintaining a relatively efficient portfolio, and it is far more attractive than forgoing a diversified portfolio and investing significantly in cryptocurrencies.

CONCLUSIONS

Outcomes are not experienced equally by investors and regret can have important implications on the perceived efficiency of portfolio outcomes. By extending the traditional portfolio optimization objective function to specifically consider regret aversion, financial advisors and institutional investors can build portfolios that align better with client preferences. This has implications in a variety of domains. For example, multi-asset solutions that do not provide context around the underlying holdings, e.g., a target-date mutual fund, may induce more regret among investors than a strategy where the individual components are clearer, e.g., some kind of custom target-date fund built using funds from the core menu of the defined contribution plan. Additionally, carving out monies specifically to invest in riskier strategies, e.g., day trading, could help satisfy issues concerning regret while not materially compromising the probability of accomplishing a financial goal such as retirement.

In closing, portfolio optimization routines have evolved to better capture risk aversion but largely have ignored regret. Investors exhibit behavioral biases to a variety of degrees, and these should be considered when developing portfolios to ensure the portfolio is efficient across a variety of preferences, beyond simply risk aversion.

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ENDNOTES
1. There are obviously other larger drivers of home bias, e.g., trading regulations, taxes, regulations, etc.
2. Cryptocurrencies would be one recent example.
3. We attempt to avoid labeling all assets as investments because many assets are highly speculative and would not necessarily meet the general criteria to be considered investments.
4. This can be accomplished easily using free tools in Excel (using the ntrand add-in: http://www.ntrand.com/normal-distribution-multi/) or R (using the rmvnorm() function of the MASS package library).
5. For example, the efficiency of non-U.S. equities tends to improve more than U.S. equities in balanced portfolios because correlations for non-U.S. bonds tend to be lower.

REFERENCES
