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Behind the Numbers: Why Optimizers Diminish Returns

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In 1952, Harry Markowitz created the foundation for modern portfolio theory and developed the mean-variance portfolio selection process. The main tool for portfolio managers using this process is the portfolio optimizer. The optimizer, using a set of means, variances and covariances, creates an "efficient frontier" that determines a portfolio of assets with the highest expected return for any given risk, which is commonly defined as variance. Its ease of use and subsequent improvement over the last half century has made it a mainstay of quantitative investment management. The current incarnation of the optimizer is truly a marvel of complexity, allowing not only the ability to control risk versus return, but also control for a myriad of other factors such as: size versus benchmark, industry and sector weight versus benchmark, currency sensitivity and leverage.

The longevity and popularity of the optimizer is admirable, and it is so well accepted that it is almost taken for granted. This popularity is interesting considering the uneven record of financial models over the last 25 years. The 1987 crash was exacerbated by the use of portfolio insurance which was a model that purported to reduce downside risk, but ignored real world trading limitations. In 1998, the demise of Long Term Capital was due to another financial model used to arbitrage bond prices, which was unable to calculate accurate results due to changing markets. The 2008 financial crisis was led by financial models that created highly rated CMO's out of low quality mortgages, which expanded a market for subprime mortgage loans. These models used risk measures, like Value-At-Risk, to determine the risk exposure of the portfolios. Apparently none of the users of these models were familiar with behavioral finance; the well-known psychological bias Framing which refers to perception of a situation being based on how information is presented. The power of framing is shown in many experiments done by Nobel Prize winner Daniel Kahneman who, along with Amos Tversky, did pioneering work on heuristics. Somehow, the portfolio optimizer has weathered these model related crashes and continues to be a staple in the investment world. However, the problems with these financial models should give some basis for questioning the wisdom of using optimizers, without questioning their potential negatives. Simply enough, are some of the factors that brought down portfolio insurance, LTCM, and CMO's present in the optimizer, but are either lost within the volatility of returns or small enough not to be readily noticed and can be made worse with use of the wrong inputs?

The academic literature on optimizers is significantly less than what would be expected from such a popular tool. A great amount of the literature on optimizers being produced by companies with an obvious bias in that they sell optimizer software, so the articles discussing potential problems with the optimization process is extremely rare. JyhHuei Lee and Dan Stefek [2008] analyze the dangers of having alpha factors and risk factors that are different, and thus causing your risk factors to lessen the power of the alphas. Kaplan and Siegel [1994] discuss that investors primarily interested in downside risk protection should not run an optimizer. However, there are significant potential problems with optimizations that should be considered before blindly delegating portfolio construction to this process.

Optimizers - Where History Always Repeats Itself

The most discussed problem with optimizers is the results of the methodology buried deep within the mathematics. Optimizers require an estimate of future returns, as well as a risk measurement that includes an estimate of the relationship of stock price moves relative to other stocks, or in technical terms, a covariance matrix. Simply put, the optimizer likes those stocks that move in the opposite direction of most stocks (low correlation), and uses those low correlation stocks to create portfolios with the optimizers view of less expected risk. The correct methodology used to create this matrix is one of the most extensively studied problems in optimizations. Ledoit and Wolf [2003] urge that it is inappropriate to use a sample covariance matrix for portfolio construction, and that without modifications, a sample covariance matrix could cause a decrease in the realized information ratio or the return relative to risk. Michaud [1989] concluded that the mean-variance optimizations tended to maximize any errors in the inputs. He also concluded that "Unconstrained MV optimization can yield results that are inferior to those of simple equal-weighting schemes." To counteract these sampling errors, most current optimizers use a covariance matrix in addition to factor structures. However, in a paper for Princeton University, Jianqing Fan, Yingying Fan and Jinchi Lv found that adding a factor structure to a high dimensional covariance matrix did not improve the estimate. They concluded, "This is somewhat surprising and is against the conventional wisdom".

Surprisingly, even with the problems listed above, there is little academic questioning about the appropriateness of using a covariance matrix based optimizer for managing stock portfolios. Most academic papers that focus on optimizer problems conclude that although not perfect, most problems can be managed and consequently optimizers are the best solution to portfolio construction.

Certain problems with the optimization process are intrinsic to the methodology. One major problem is that the covariance matrix assumes the future will look like the past, i.e. companies whose prices move in opposite direction of the market will continue to retain low correlations. In the real world however, the reason that low correlations happen is usually due to a one time outlier event (Black Swan), such as: death of a founder, hurricane or fire destroying production facilities, oil spills, discovery of a new energy source, scandal, product safety problems, merger or a wildly successful or spectacularly failed product launch. The important factor is that these events are not repeatable or predictable, but the optimizer assumes that they are and will be in the future. Low correlation stocks are like manna from heaven for creating low risk portfolios, and these low correlation stock are very attractive and will be included in almost any optimized portfolio. The downside is that the low correlation does not continue because it is predicated on a one-time event. Thus, the result is that most optimized portfolios end up with higher actual volatility than the predicted volatility.

Another practical problem with optimizers is trying to create portfolios with fixed risk relative to a given benchmark. Here again the sample period and the data set used has a great impact on the actual stocks included in the portfolio. During sample periods when stock volatility is high, the process assumes that volatility will stay high. Although this high level of volatility may continue in the short run, in the longer term, which is a time frame more accurate to stock investments, volatility will be mean reverting. Periods of high stock volatility will be followed by a period of lower volatility. However, when using an optimizer, during periods of high volatility, the optimizer will favor companies with low volatility to keep the portfolio within risk targets. These low volatility companies will then need to be sold as the market mean reverts to a lower risk environment, necessitating purchasing high volatility stocks to increase portfolio risk.

The problem is that the optimizer is a poor manager when dealing with events outside the range of the sample period (the time period used for the covariance matrix). If a major event, such as a banking crisis, occurs without a similar one happening during the sample period, the optimizer for purposes of our discussion "becomes confused", all of its assumptions are based on events occurring in a future that mimics the past. And the past rarely repeats in a similar manner, the housing crisis in 2008 has not repeated, and the next crisis will likely have a different cause and outcome.

Skinny Cows

Perhaps the greatest problem for optimizers is that what is good for a few may be bad for the many. The model backing an optimizer creates a risk/benefit analysis which tries to predict an opportunity for future superior returns (which is why it became so popular). However it is a limited opportunity, not unlike a good piece of pasture land. Using the pasture as a metaphor, if the farmer puts just a few cows on the pasture, the cows do very well, but if thousands of cows are put on the pasture you end up with a lot of skinny cows. If only a few investment managers use optimizers, these managers would benefit from the risk/return tradeoff that optimizers provide. However, at any point in time, hundreds of managers and billions of dollars are invested using optimizers in quantitative, enhanced index and index products, and these managers end up chasing the same stocks at the same time because the sample period showed certain companies as having positive risk characteristics. In effect, the popularity of the mean-variance optimization will cause certain stocks to be bid up due to their risk characteristics, limiting the returns of companies using the process.

Not considering the impact of the model on the market, and the data set that the model is based on, is a continuing problem with financial modelers and has contributed to some of the great failures in portfolio management. Most quantitative models assume that the model itself will have no impact on what it is trying to analyze. While this assumption is true when only a few people are using the process, a successful modeling process leads to its widespread use or copying.

The 1987 crash is a prime example: portfolio insurance was a very popular method of limiting downside returns. However when prices started to decline in October, the portfolio insurance model exacerbated the problem by forcing hundreds, if not thousands of users of the process, to sell great amounts of futures into a falling market. The forced selling by the model had each manager's sales followed by another sale, pushing prices down as it tried to manage the strategy in an optimal manner.

Some of the current financial crisis can also be attributed to financial models assuming the model will not impact the market. Financial models were used to take groups of low rated mortgages and combine them to create CMO's that had significantly higher ratings (sometimes AAA), basically turning garbage into gold. The original model was probably correct, however the unintended impact was that by turning garbage into gold, the model created a huge market for low rated mortgages which did not exist previously. This started the frenzy of easy financing standards since now the initiator of the mortgage did not have to hold it on their balance sheet and could find a ready market as high rated paper. In the end, this did not turn out well.

Because the most popular optimizers use the same mathematical formulas, every company using that optimizer will unknowingly favor certain stocks simply because of their risk characteristics (companies with low correlations and companies with low volatility in volatile industries are particularly attractive). The billions in assets using optimizers spread the benefits of optimizers very thin and possibly end up creating perverse pricing that actually reduces portfolio performance. Since all optimizers use the same principals, *the capacity of companies using optimizers need to be considered in total, not individually*.

The problem is even greater when you consider a quirk of most commercially available optimizers. The covariance matrix for many providers is only updated on a monthly basis. The matrix is created using a rolling window comparing stocks over a certain time period. Thus, if a company is rolling off a particularly volatile period or is rolling off a period that caused its correlation to be low, then that company will have a major change in its risk profile. With the large quantity of assets using the optimization process, significant changes in a company's risk profile will cause a month-long buying or selling frenzy for this stock, changing the stock price steadily during the month. As an investment manager, it is perilous to be trading this stock at the end of the month after all the other optimizer managers have already influenced the price. So funds using optimizers should find it advantageous to trade at the beginning of the month, before the other optimizer managers move the stock price.

Size Does Matter

A common factor added to most commercially available optimization programs is the ability to control for the capitalization of the output to be similar to the universe or benchmark. However, the methodology used to create similar capitalizations creates another problem for portfolio managers. Although most large cap stocks could be broken up into a series of smaller companies, bringing into question the logic of controlling capitalization in the first place, larger companies do have certain advantages. Large companies have better access to capital, often have operating efficiencies, and sometimes can create barriers to entry for smaller firms. In practice optimizers do a poor job of managing the capitalization of a portfolio. The benefits of size tend to be very industry specific; being the largest company in some industries can be very advantageous, whereas in other industries being the largest has little to no advantage. This industry effect is why there is only two large commercial aircraft manufactures in the entire world, but dry cleaning companies (and most service companies) are usually locally owned. The problem optimizers make is that in industries where being the largest is a distinct advantage, the big companies tend to sell at a premium. This premium makes them less attractive if a manager is using P/E or other value measures. So the optimizer, in an attempt to match the portfolio capitalization to the benchmark, *will underweight the largest stocks in industries, where being the largest is an advantage, and overweight the largest stocks in industries, where size is little or no advantage - Exactly the opposite of what should be done.*

Conclusion

Michaud in his article notes many simple reasons for not using an MV optimizer, including politically not wanting to subordinate decision making to a computer, and that the optimized portfolios created unintuitive stock choices. This article posits that there are numerous other potential problems with the portfolio optimizer when used to create stock portfolios, and many of these have been understudied in the academic research.

Some of the questions brought out in this article show the potential adverse effects on performance caused by a counter-optimal portfolio created by an optimizer. The history of investment models shows that without careful supervision, these models tend to create unintended consequences to the users demise. The optimizer may have avoided some of these pitfalls due to its complexity, diversification, and the difficulty of proving that adverse stock selection was due to problems with the optimizer, not the alpha generation process. However, future research should be conducted to confirm the ideas presented in this article. Certain problems, such as the size effect, can potentially be areas of future study. Proving the problem of the optimizer's effect on the market itself, by favoring certain companies, will probably be difficult, and possibly may only be surmised by the lagging performance of managers using the process.

The final question is whether the optimizer is appropriate for choosing stocks, or can the benefits of risk aversion and diversification be accomplished without the negative problems associated with mean-variance optimizations. Most benefits for risk control can be accomplished by industry/sector neutrality versus a benchmark and reasonable stock weights relative to benchmark weights. Attempting to manage stocks using an optimizer, with numerous other managers using the same algorithms, and consequently relying on the same stocks, is a recipe for failure for both risk and return. In the end, does the optimizer create an illusion of risk control with the reality of sub-par performance?

Alternatives

Since the future is unknown and can vary dramatically from the past, trying to control risk within narrow bands is probably a fool's errand. Is it reasonable to create risk estimates with decimal places of precision, as is possible with currently available programs? Would it be better for risk be viewed in much broader terms such as low, medium or high? The focus on risk control in the past few decades has provided useful tools to control risk that are not limited to optimizers. Considering the weight of stocks in the benchmark, and only allowing certain deviations from benchmark weight, can control risk without the need of optimizers. In addition, controlling industry and sector weights, and ensuring that average capitalization is similar to the benchmark, are excellent risk techniques that can be used for any portfolio. Alternatives to optimizers are available and rely on factor constraints that have proven useful for risk controlled portfolios.

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About Hillcrest Asset Management

The Hillcrest Portfolio Team utilizes their combined behavioral finance expertise to create all client portfolios. Hillcrest remains guided by a fundamental belief that stocks deviate from their fair value due to behavioral biases and stocks follow the behavioral cycle of stock movements. We combine model-driven behavioral analysis with traditional fundamental research to build on the strengths of both approaches. Our goal is to add value equally through both behavioral models and fundamental stock research. Results reflect Hillcrest's expertise in successfully utilizing these concepts in the portfolio management process.

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