Hunting for Black Swans

Comparing Probability Outcomes of Capital Market Assumptions to Historical Observations

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In 2002, we released my whitepaper entitled, *Are You Modeling What You Intended? Building Capital Market Assumptions for Monte Carlo Simulations*. That paper highlighted numerous errors that are regularly made throughout the financial services industry when it comes to building capital market assumptions (CMAs) for use in various mathematical modeling tools like mean variance optimizers and in particular for use in running Monte Carlo simulations for wealth management plans. The key premises of what we pointed out in that paper are sound and remain intact today. I am not going to rewrite that which has already been written nor reassemble the extensive data and research to support it since the paper that contains all of that information is still available. Instead, I will merely highlight some of the key tenets that are fully supported by that paper, explain what discoveries and improvements we have made since that time, and demonstrate that our revisions to our CMAs (however small they may be) improve on modeling what we intended when using these capital market assumptions in Monte Carlo simulations to deliver Wealthcare advice. These revised assumptions meet the tenets of both our past research and our new discoveries.

Some of the key premises in my original paper that are still true today are:

1. **The less data you have the more uncertainty you have about its reliability of reflecting the nature of the asset class, but merely using the longest period may also introduce errors in the resulting probability distribution.**

2. **Whatever assumptions you come up with will be "wrong" to some extent and thus the effort should be focused on minimizing potential "wrongness" by avoiding the introduction of spurious errors which cause inconsistencies in simulated outcomes.**

3. **Test your assumptions in the simulation engine and compare the probability distribution output to historical observations to validate that the range of the limited historical data rationally falls within the broader range of the simulations.**

4. **Forecasts and assumptions of mean reversion do not fit well into an advice process designed around managing wealth and lifestyle choices assuming continuous uncertainty.**

A brief synopsis of what is supported in the original paper for each of these premises follows and then we will move on to how and why some improvements have been made in our new assumptions.

The first premise we will summarize is the use of insufficient data to draw a valid conclusion, the uncertainty impact of such limited data, as well as the errors that can still be introduced even with what would otherwise seem to be sufficient data.

Over the years I have heard from many readers of the paper asking for a magical number of how much data is sufficient to form a basis for building CMAs. Of course, there really is no right answer to this and the amount of uncertainty in the class itself can dictate a need for more data. Then there is the corollary premise that the longest available data set can be just as misleading as a sample of short term data. Read the original paper to review the evidence supporting both of these premises. The net result though is that when one is building capital market assumptions that are designed with the intention of modeling the uncertainty of the nature of the returns for a portfolio allocation, that uncertainty is controlled by the portfolio standard deviation and may need significant modification from what is merely observed over shorter term data sets. Likewise, even long term data sets may have biases in the data and *the method* used to construct assumptions should attempt to compensate for outlier observations to avoid inappropriate shifting of the entire probability distribution. Thus, the method one uses should help compensate for both of the problems and if the method makes no such attempt it is likely the person creating the assumptions *will be used by the data* instead of *using the data to create a sound assumption*. For more realistic assumptions, one must hunt for sources of influence, errors and skewness in the data, and it is not as easy as simply taking an average of one year returns no matter how long a dataset you have, or what the text books over simplify.

Whatever assumptions you come up with will be "wrong" to some extent and thus the effort should be focused on minimizing potential "wrongness" by avoiding the introduction of spurious errors which cause inconsistencies in simulated outcomes.

Sometimes, when we are poring over mountains of data elements it is easy to get lost among the data trees and completely lose sight of the forest of the macro capital markets. In many cases, it is better to use a similar proxy and adjust the assumptions for what is unique in the asset class. For example, there are historical data sets showing that foreign stocks have a higher return than domestic stocks (there are lower ones too). If you are making the assumption that on average companies in foreign countries will produce higher returns, you are also assuming that the average company that moved their headquarters overseas would appreciate more than if it did not. The converse is true as well. This is obviously absurd but it is an example of missing the common stock forest while staring at the foreign stock trees. Companies attempt to make profits no matter where their headquarters are, but those profits may be subject to currency risk when they are repatriated to U.S. investors as shareholders and thus have more uncertainty (standard deviation) and will not perfectly correlate (creating an opportunity to blend the two in some rational proportion to optimize a risk and return trade off). But merely taking an observation of one time period, be it relatively long or short, could certainly cause some erroneous and unintended modeling errors at a macro level.

Another example of introducing spurious data that multiply into unintended modeling errors is attempting to model assumptions at sub macro asset class levels. The markets of 2008 proved this point for me as I warned advisors about seven years ago. Our indexed risk averse portfolio was down about 3% in 2008 even with 30% equity exposure. Our balanced income portfolio with 45% in stocks was down around 11% and our balanced portfolio with 60% in equities was down around 18%. We only had four pie slices in these portfolios consisting of domestic stocks, foreign stocks, government bonds and cash. We did no market timing and merely passively accepted the market's results. Yet, many supposedly "more diversified portfolios" with ten or twenty pie slices were down more than twice as much with similar equity exposure. The reason such supposedly more diversified portfolios performed poorly was not because of "asymmetric correlations" in the market shock as so many have professed. **The cause was that the model allocation itself was created from erroneous capital market assumptions** (often based on tiny snapshots of data, or even worse, uncertain forecasts of asset class behavior). If you have bad assumptions going into your process of creating a model allocation, the allocation will not behave as anticipated. Well reasoned assumptions should have modeled the extremes that result in such "asymmetric correlation" markets. You can't blame the markets' high covariance and poor results relative to your model when your allocation model should have anticipated this effect, as ours did. All of those assumptions of sub class pieces need to add up to the market whole. Few do. **Do not confuse pieces with the whole.**

When it comes to modeling allocations based on some assumed inputs, taking common stocks and breaking them into growth, value and core along with large, mid, small and micro cap requires many more inputs (assumptions) than the macro class of domestic stocks of which they are all members *and must by definition add up in proportion to their market cap*. To model the returns of a 100% domestic equity portfolio, all I need is two very well researched assumptions as inputs: the risk and return for domestic equities. No matter how well I research it, I know my assumptions will be wrong. Thus, in modeling domestic stocks I am only introducing two assumption errors, and there is a lot of good data to examine, so the amount of my assumption errors should be fairly small if I am diligent. But, for each piece of domestic equities I attempt to model, I need to come up with risk, return and correlation coefficient assumptions to all of the other pieces of domestic equities, often with much smaller data sets. The number of assumptions I am making (each of which will introduce errors) for a total domestic equity portfolio based only on large cap, mid cap, small cap and micro cap stocks explodes from the two points of error introduction of just risk and return for domestic equities to FOURTEEN assumptions that each introduce a source of assumption errors. While I attempted to compensate for this in our 2002 capital market assumptions by assuming the same risk and return for growth and value as I had for the core market cap based index, I admit that I did let the trees of the long term data I had back to 1926 for the market cap based assumptions permit me to introduce some small unintended errors. Later we will show you how we have now corrected for both of these unintended modeling errors.

Test your assumptions in the simulation engine and compare the probability distribution output to historical observations to validate that the range of the limited historical data rationally falls within the broader range of the simulations.

It is easy to just accept a simple method (particularly when you have a lot of data) like just using the average return and standard deviation and plough forward. This has a marketability advantage because it is easy to explain, sounds compelling and text books back it up too. But, without checking what happens when you use such a method in the simulations *as you will be using them for wealth management clients,* you can easily permit unintended shifts in the shape of the probability distribution resulting in erroneous confidence levels.

For example, while the text books might tell you that you should simply take the average of one year periods and standard deviation of those one year returns as an assumption, it is worthwhile to compare that to something closer to how these assumptions are being used as in a longer term wealth management plan. For large cap stocks from 1926 through 2008 based on monthly data, the mean return was 11.57% and the standard deviation was 20.59% which produces a geometric mean (compound return) of 9.72%. In looking at the probability distribution of the 985 one year historical periods (based on monthly data), this appears to be a reasonable estimate (see *Table 1*).

Table 1 – Percentage of historical twelve month observations for large cap stocks based on predicted normal and log normal distributions using simple average return and standard deviation.

	Difference from Normal Distribution	Normal Distribution	Difference from LN Distribution	Log Normal Distribution
Within 1 SD	1.6%	68.20%	0.6%	69.23%
Within 2 SD	-0.4%	95.45%	-0.7%	95.71%
Within 3 SD	-0.6%	99.73%	-0.3%	99.38%
Within 4 SD	-0.197%	99.994%	-0.110%	99.907%
<- 1 SD	-0.875%	15.90%	-0.283%	15.31%
>+1 SD	-0.773%	15.90%	-0.332%	15.46%
<- 2 SD	1.075%	2.275%	2.586%	0.765%
>+2 SD	-0.651%	2.275%	-1.905%	3.529%
<- 3 SD	0.373%	0.1350%	0.507%	0.0008%
>+3 SD	0.271%	0.1350%	-0.216%	0.6225%
<- 4 SD	-0.003%	0.003%	0.000%	0.000%
>+4 SD	0.200%	0.003%	0.110%	0.093%
< Mean	-1.1%	50%	-4.7%	53.6%
> Mean	1.1%	50%	4.7%	46.4%

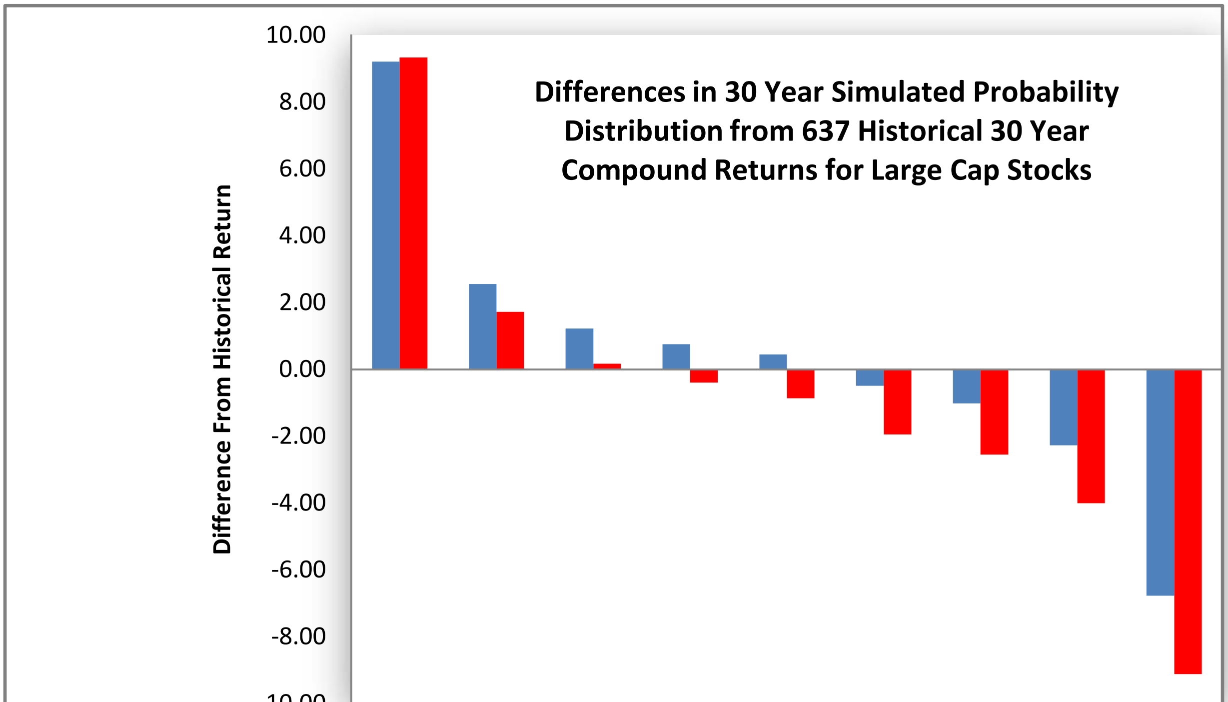
For *one year returns,* the counts of the limited historical data relative to what would be statistically predicted are not that far apart and probably are not meaningful considering the wide range of what would be simulated. Also, because we are using rolling twelve month periods, short term historical market "shocks" are recounted several times in the observations. So much for Black Swans with fat tails! This is especially true when you consider that with Wealthcare we are targeting a workable range of probabilities of between 75%-90% confidence (our confidence comfort zone). But, while these assumptions predict one year observations reasonably close to historical observations, the compound return these assumptions create (which would fall toward the middle of a normal distribution) was 9.72%. Interestingly, *72.5% of the 637 historical 30 year periods* produced a compound return higher than this. In a log normal distribution as we simulate, the median compound return would be 9.52% of which 80% of the historical 30 year periods produced a higher return. *Even ten year historical data shows half of the 877 ten year periods exceed this return by more than 1.15%.* Using this simple average text book input would have us modeling wealth management plans that would simulate half of the trials being worse than what occurred in only 20% of all 30 year historical observations. We think this is too conservative and causes many unintended consequences.

These simple average inputs, when used to continuously make choices about balancing life goals, would cause needless sacrifice to an investor's lifestyle. It may encourage the investor to take more risk than necessary to try to compensate for the excessively conservative assumptions, wreaking havoc in extreme markets like 2008. As an industry, being conservative in assumptions was prudent before we were modeling the uncertainty of the range of returns and the timing risk introduced with Monte Carlo simulation. **Being excessively conservative in assumptions when you are modeling the uncertainty does nothing other than needlessly sacrifice an investor's life**, another premise from the original paper.

The data exists to discover this if you examine it closely. Of all one year periods, 50% were greater than 11.91% and 45% were higher than 14.61%. While the average of all one year returns was 11.57%, the average of the 877 ten year mean returns was 12.17%. In fact, 50% of the ten year mean returns were over 12.50%. Also, the average standard deviation of all ten year periods was 18.51% and the median was 16.45%. By testing what comes of out the simulations with such inputs and contrasting this to history, we can see whether some outlier observations might be skewing the long term data causing us to be either excessively conservative or overly aggressive, depending on the asset class and the data. Using the median 10 year return of 12.50% as an input and the average of 877 ten year standard deviation observations of 18.51% might smooth some of this outlier noise in the one year data, and permit the simulation engine to do its work in simulating extremes we have not yet historically observed. Now, many will protest that in so doing we are assuming a return that is nearly one percent higher and a standard deviation that is two percent lower. But, this smoothing method compensates for some of the biggest historical observation errors in even the one year data. In Table 1, observe that for the log normal distribution (you can't lose more than 100% in a long stock position thus why normal distributions are not quite as good a tool) there was a shortage of 4.7% (46 one year periods) of returns below the mean and thus an excess of 46 observations above the mean. With the smoothing effect of using the median ten year mean return and average ten year standard deviation, the method indeed results in a higher mean and lower standard deviation than would result from the simple average, but the smoothing method corrects a significant amount of this historical one year observational error. That error is reduced from 4.7% to 1.7% (a shortage of 17 historical observations for returns less than the mean and an excess of 17 observations above the mean). Do we need to be more conservative when we are already measuring confidence levels toward the conservative tail? Even the outlier counts do not change much. The assumptions only cause one additional four standard deviation historical observation, and the net of all positive and negative standard deviation counts from what the assumptions would predict drops from -51 observations (5.2%) to -47 observations (4.8%). While this is a slight improvement, it is not materially different than the simple average method when applied throughout the distribution. We could debate one or two percent observation shifts throughout the probability distribution and whether improvements in some one standard deviation events are offset by small increases in observational errors in two standard deviation events. But, that is all just one year data and what we are building these assumptions for is generally meant to model a much longer wealth management plan.

Here, this smoothing methodology for building capital market assumptions makes some significant corrections for how we are using them in crafting wealth management advice (see *Chart 1*).

Chart 1 – Comparing the difference from historical compound returns in simulation output based on the smoothing method and simple average method of building capital market assumptions.

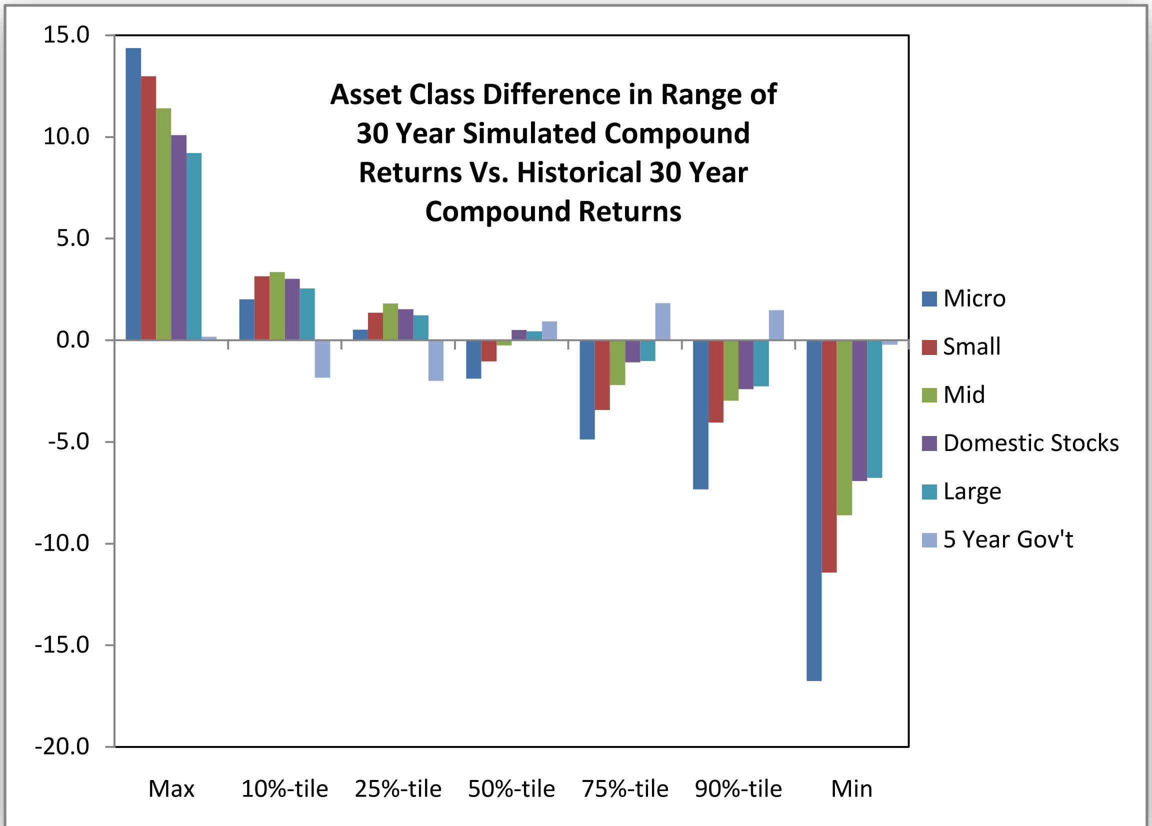


	Max	10%-tile	25%-tile	33%-tile	50%-tile	66%-tile	75%-tile	90%-tile	Min
Smoothing Method	9.21	2.56	1.23	0.76	0.45	-0.49	-1.02	-2.27	-6.77
Simple Average Method	9.34	1.73	0.17	-0.39	-0.86	-1.95	-2.55	-4.00	-9.12

When we are simulating 30,000 years of investing, the range of outcomes should be wider on both tails than what we can observe with our limited history. Both methods of building capital market assumptions demonstrate this effect. Also, as the volatility of the asset class increases, the extent of the difference should expand (for example the range of simulated differences for small cap and mid cap stocks should be wider than that of large cap stocks, see *Chart 2*). Still, we need to consider where we are choosing to measure things in the advice process. With the smoothing method of building assumptions, at the 75th percentile (the bottom of our recommended confidence zone) we find that the 30 year return of 8.64% is less than 94% of all 637 historical thirty year periods. Is it necessary to plan an investor's life around starting their wealth management plan at what would be statistically near the absolute worst quarter in history? With the smoothing method, in 1,000 trials, 250 would be simulated that are worse than the 8.64% compound return, when only 38 of 637 were observed historically (also remember this is based on recounting short term shocks in rolling monthly data).

At the 90th percentile (the top of our recommended confidence zone which defines being "overfunded" or indicates the wealth management plan is making "needless sacrifice") **the simulated return of <u>6.79% is 0.43% less</u> than starting at the absolute worst month in history.** This means that our "aggressive" higher return and lower standard deviation based on the smoothing method will simulate 100 of 1,000 trials being nearly a half percent less than starting a 30 year plan in the absolute worst historical month. Do we need to be more conservative than this? If we are already simulating black swans with fatter tails than were ever observed, if we are using a process that constantly monitors the effect of markets on the choices one would need to make because of nearly certain market misbehavior; what are we accomplishing by creating assumptions that force us to assume even more fat tailed black swans — other than causing investors to needlessly sacrifice their lifestyle or encouraging them to chase higher returning portfolio allocations that subject them to needless investment risk?

Chart 2- Difference in simulated range of 30 year compound returns to historical returns for various asset classes based on Wealthcare Capital Management's new assumptions.



Forecasts and assumptions of mean reversion do not fit well into an advice process designed around managing wealth and lifestyle choices assuming continuous uncertainty.

Inherent in the Wealthcare process is the notion that the markets are continuously uncertain. This means that the process *always is expecting the unexpected.* No matter what the markets have recently done, be it rallying to new highs or being decimated by losses, the assumption is that we cannot change the past and the odds of an unexpected Great Depression or Tech Bubble are no more nor less than they were yesterday, or last year. This also means that just because markets declined over the last year (or two years, or three years) we are not going to assume that things will be better going forward (the result of assuming mean reversion). Likewise, we are not going to assume some economic model, relative valuation model, or Ouija board for that matter will be a better estimate of the total amount of uncertainty of the capital markets. Any capital market assumptions that deviate from those assumptions that would otherwise simulate the total possible distribution of outcomes would by definition shift the entire distribution in some manner and thus will skew the uncertainty away, or toward, whatever bias the forecast contains. While such forecasts may have some value if you are in the business of forecasting what will happen (and thus are paid for being right about such forecasting ability), it is contradictory to mix the certainty of a forecast with a model that simulates uncertainty. As we saw in the previous example (*Chart 1* and *Table 1*), a 1.00% adjustment to mean return and 2.00% adjustment in standard deviation can materially skew the entire probability distribution of long term wealth management plans relative to history. Do we really wish to simulate half of all trials being worse than 80% of historical observations and a third of all trials being worse than the worst historical period? Or, if we are overly aggressive in our forecast, do we really want to simulate half of all trials being better than 80% of all historical observations and a third of the trials better than the best historical observation? Such extremes easily occur when one fiddles with sometimes small changes to the capital market assumptions.

Why Change Assumptions?

If your assumptions reflect diligence in all of these key premises, they should not require any changes, unless:

1. Better data becomes available
2. Errors are discovered and there is a means of correcting them
3. New data of recent observations fall outside of what would be statistically simulated with prior assumptions.

Observe that having just one more year of data is not reason in itself to justify changing the assumptions unless it meets criteria number three. Since the 2002 paper, we did not have any observations of capital market behavior we were not already simulating, including 2008. The recent market performance is not quite "the 100 year flood" as those avoiding blame keep screaming, but it is close. The ten year compound return for large cap stocks was -1.57% ending in 2008, near some of the worst in history. But, there were 17 ten year periods back to 1926 with lower returns, based on monthly data. Of course all of these observations included the Great Depression so the ten year period ending in 2008 was indeed the worst excluding that environment. With well reasoned assumptions, we would be simulating something similar, and with our past (and new assumptions) we simulate such environments occurring. Also, we have already shown how much more severely and frequently poor markets are simulated with our assumptions relative to what we have historically observed over longer time periods. This means criteria number three was not a catalyst to amend our assumptions.

Data availability has improved somewhat. The Center for Research in Security Prices released a completely revised history back to 1926 in 2007. This release of minor revisions in itself also did not justify changing the assumptions because the statistical impact was immaterial from our evaluation and use of the data in our Wealthcare process.

The catalyst for us to modify our assumptions came from a discovery we made when we replaced the numerous ETFs in our portfolios that were designed to replicate total domestic equities with a single domestic equity ETF to harvest tax losses and lower expenses for our asset management clients. In so doing, we discovered some unintended errors in our capital market assumptions that unfortunately were not very easy to solve.

Problems we discovered with sound assumptions

Our previous assumptions met all of the criteria we already outlined as key premises needed to minimize unintended errors. For each macro asset class with long term data, we used a smoothing method to create the return and risk assumption by averaging the mean return and standard deviation of all ten year periods to avoid outlier observations that would skew the distribution in the simple average method. The assumptions for each class were run through our engine and the simulated results were compared to historical ranges over various time periods to ensure that all historical results fell within the simulated range, and that the difference between simulated and historical ranges increased at the tails as the volatility of the asset class increased while the middle of distribution fell near the middle of historical averages. Proxies were used when historical data was insufficient and such resulting assumptions would not be excessively selected or avoided in a mean variance optimizer (for example, with growth and value styles of various market caps having the same risk and return but not perfectly correlated, both would be selected by the optimizer.) No forecasts or predictions of mean reversion were used that would introduce biases that would shift the probability range toward or away from any potential uncertainty we were modeling.

For each asset class, we knew the assumptions would be wrong, but in applying these disciplines and tests, we minimized potential "wrongness" so that our targeted confidence range of 75%-90% would reasonably capture the extent of the errors we were introducing in our assumptions for wealth management plans built near the center (81-84% confidence) of that range. We even went to the step of testing portfolio allocations based on the individual asset class assumptions by simulating the outcomes of those portfolio allocations to validate that the historical ranges fell within the simulated ranges at the portfolio level, just as they did at that asset class level. Our previous assumptions passed all of these criteria, which is probably why our new assumptions, in most cases, do not produce materially different results. However, there is one thing we did not validate in our previous assumptions that we have now corrected.

The whole must equal the sum of its parts — getting lost among the data trees of the capital market forest.

With all of this testing of assumptions at the detailed asset class level and even at the portfolio allocation level, I fell victim to getting lost among data trees and lost sight of the forest in which those trees belonged. This simple oversight was exposed to us in replacing our collection of various domestic ETFs that were assembled to essentially replicate total domestic equities with a single total domestic equity ETF to lower expenses, tracking error and rebalancing costs. We never built capital market assumptions for total domestic equities. There was no need for it. Everyone was modeling by market cap and style so we just built assumptions to accommodate that. But now, with our asset management portfolios using a total domestic equity ETF, we thought our wealth management platform should be able to model this macro asset class alone and needed to create assumptions for total domestic equities. With all of the other sub-asset classes passing our litany of tests, we thought we would merely apply the same method to domestic equities. But when we did this, we discovered things did not add up.

Our previous testing showed that, for example, the simulations resulting from our assumptions based on asset classes[1] for a portfolio allocation of 2.5% small cap, 7% mid cap, 40.5% large cap, 20% long treasuries and 30% in five year treasuries ended up passing all of the criteria outlined when those same asset classes were assembled into historical portfolios. Yet, when we replaced all of the market cap based stock allocations with assumptions built for total domestic equities in the exact same manner, the results were different…too different to ignore. In retrospect, I should have originally tested whether replacing all of the market cap pieces with total domestic equities would come up with approximately the same answer. It would be a commonsense thing to check. But I was lost among the data trees of the asset class forest. I know mathematically the whole must equal the sum of its parts, but the results were surprisingly different, too different to be satisfactory from a statistical perspective. Something was wrong somewhere. The assumptions for some of the market cap pieces were still skewed despite our verification testing relative to history for the asset class. This must mean the smoothing method we used did not sufficiently correct for outlier observations for at least some of the sub asset classes.

To explore this further, the first thing I tested was eliminating our assumptions from the equation and merely looked at the all of the data and statistics based only on history for 985 one year periods back to 1926 for total domestic equities compared to a portfolio comprised of the average weights of the market cap components based on annual rebalancing. In theory, this should expose what our smoothing method would sufficiently compensate for and what it would not. The average ten year standard deviation observed in either allocation was within one basis point (the simple average standard deviation between the two differed by 23 basis points and in both cases was more than 210 basis points higher than the smoothing method, another example of how simple average methods skew what we are attempting to model). This appeared to mean that our method was sufficiently correcting the effect of outlier observations at least in terms of modeling standard deviation.

Various return statistics pointed to the potential for a small amount of error being introduced by our smoothing method of taking the average of 877 ten year returns. The simple average of one year returns differed (from what should have been essentially the same result) by about 13 basis points. The average of ten year mean returns also differed by a similar amount. The difference for both portfolios between the historical simple average and historical smoothed average was about the same. Finally, the median ten year average return was higher than the average of ten year returns by 52 to 56 basis points. Again, this is too close to really point to a significant error

[1] We have switched our market cap definitions to exactly match the CRSP definitions instead of our past approximation of CRSP breakpoints made to map to popular indices we previously used.

in the methodology and acceptable from a statistical perspective. Even the median ten year compound returns were within 4 basis points. On the surface, this appeared to show that whatever error we were introducing by our method, it was not material whether we looked at the whole portfolio or a portfolio created by adding up the pieces. Yet, when these same methods were used to create assumptions for individual asset classes, suddenly the pieces no longer added up to the whole, even though they should within a reasonable approximation as shown by the pure historical data.

Looking across the capital market forest

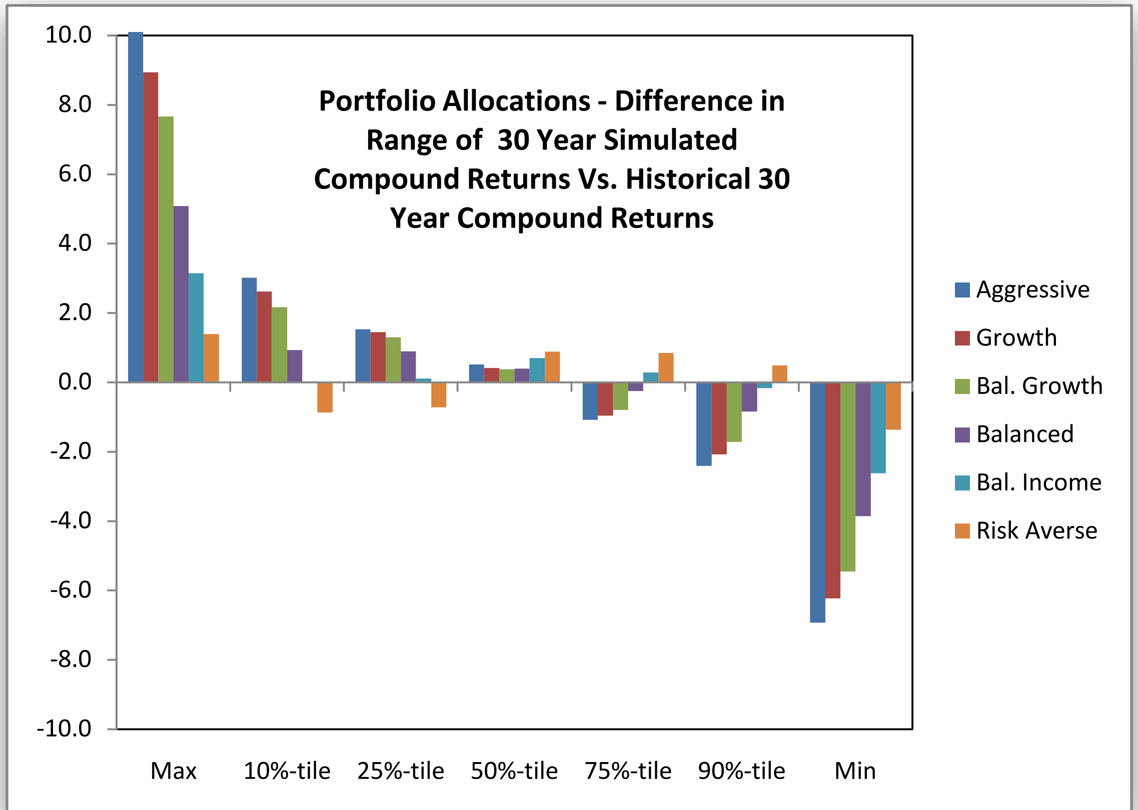
This caused us to examine where the method itself appeared to differ in the introduced estimation error *between* asset classes. These relationships of the statistics appeared similar between most of the asset classes just as they did for portfolios of asset classes. The average of ten year returns were somewhat higher than the one year average returns. For total domestic equities it was 64 basis points higher and for large cap stocks it was 60 basis points higher. For the somewhat more volatile midcap stocks it was 68 basis points higher. But, for small and micro caps, it was 103 basis points higher. Might this point to the method not sufficiently compensating for outliers?

Similarly, the *median* of 877 ten year average returns was between 20 and 56 basis points higher than the ten year *averages*, except again for small and micro cap. The median 10 year average return for small caps was 79 basis points LOWER (not higher) than the average of ten year periods and for micro cap it was a whopping 274 basis points lower.

All of this evidence caused us to rethink how we were compensating for outliers in the data observations with our smoothing methods. Any of these numbers can be used as inputs into the simulation engine and compared to historical one, ten or thirty year historical observations and likewise any of these inputs will introduce various statistical errors relative to observed history of differing amounts at differing points in the probability distribution. Remember, the assumptions will be wrong but what we need to do is minimize the extent of wrongness our method is introducing, considering *what* we are modeling (long term wealth management plans) and *where* we are measuring it (in the comfort zone) within the distribution. **Regardless of the method, mathematical truisms like the pieces adding up to the whole should not permit statistically significant differences in simulated outcomes.**

The discovery that the method of creating assumptions, no matter how closely one scrutinizes it, can still create some weird outcomes caused me to examine all of the pieces that should add up to the whole. Shouldn't a portfolio that is 50% large value and 50% large growth add up to something that would be statistically equivalent to large cap as a whole? Shouldn't the same hold true for mid cap value and mid cap growth, etc.? And then, while we are tearing this apart, if we discovered that the method used for pieces of total domestic equities caused inconsistent assumptions that did not make the pieces add up to the whole, what about the even more problematic nature of fixed income securities? The original paper on capital market assumptions addresses the fact that fixed income securities are not log normally distributed, are highly serially correlated (unlike the randomness of equity markets) and when portfolios are modeled with more than 75% fixed income, the shape of the distribution becomes too distorted from reality for use in wealth management planning with a log normal distribution. With at least 25% equities, the uncertainty of stocks makes the error introduced by fixed income statistically insignificant for our purposes[2].

Chart 3- Difference in simulated outcomes from historical ranges of 30 year compound returns for portfolio allocations ranging from 30% stocks (Risk Averse) to 100% stocks (Aggressive) based on our new capital market assumptions.



This started me wondering first on how I could have missed something that should be (at least in retrospect) so obvious, and then got me curious about how many other capital market assumptions by other major reputable firms had the same problem. I pored through the published capital market assumptions from several major firms. I excluded those that were based on short term forecasts, predictions of mean reversion and the like, which would have almost no chance of adding up, and focused on only those published capital market assumptions that represented the "long term normal" for the asset classes. Plugging these risk, return and correlation assumptions into our portfolio calculator (email us if you would like a free copy of this excel spreadsheet at support@wealthcarecapital.com) I found that NOT ONE of our

[2] See 5 Year Government bonds in *Chart 2*, and our Risk Averse portfolio allocation in *Chart 3*. The bonds have nearly a 2% annualized misfit at the 90th percentile in *Chart 2*, reduced to less than 61 basis points at the 90th percentile and fully corrected at the end of the tail to be 118 basis points under the worst of history for the Risk Averse portfolio as shown in *Chart 3*.

competitors or even any of the major firms had assumptions that did not introduce a statistically significant error in modeling pieces that should add up to the whole. For example, does it make sense that one would pick up 31 basis points of return by merely drawing a line in the middle of large cap stocks even though I still owned the same thing in identical proportion to the whole? How about getting the free lunch of decreasing my standard deviation by 145 basis points and picking up 27 basis points in compound return merely by owning small cap blend in the form of equal weights of small cap value and growth? The pieces sometimes worked the opposite way in another firm's assumptions where splitting large cap into equal growth and value pieces increased the standard deviation by 26 basis points.

While there will be some small statistically insignificant errors based on rounding and tweaking assumptions to make sure the correlation coefficients along with risk and return assumptions pass a Cholesky decomposition, the errors I observed were much larger and thus statistically significant. (Even our new assumptions introduce +/- 9 basis points on mean return, +/- 6 basis points on standard deviation and +/- 9 basis points on geometric mean depending on how you reassemble total domestic equities from all of the various choices you have in recreating domestic equities from market cap and style components. Still, with our new CMAs, all style components perfectly match their market cap blends if weighted in equal proportion.)

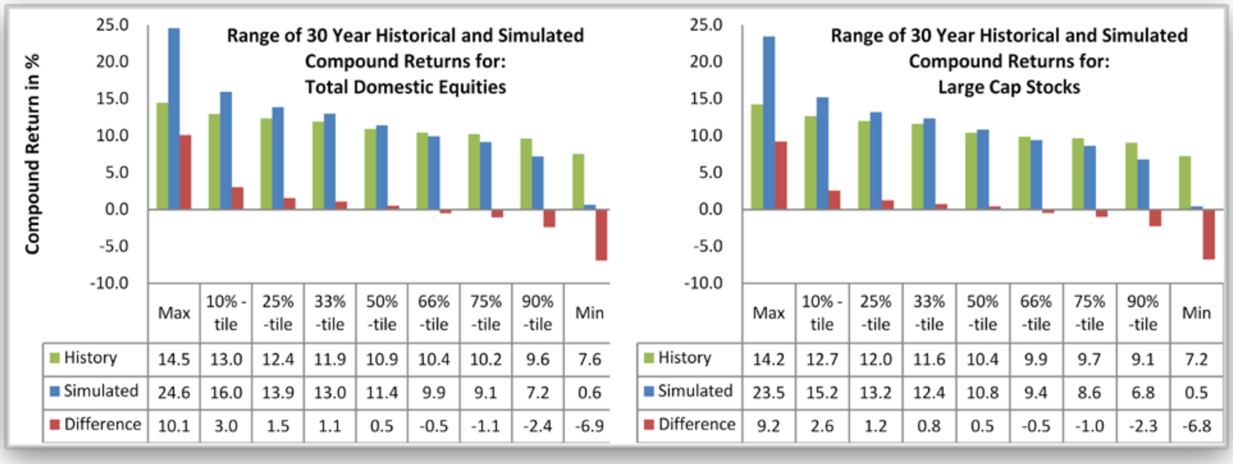
The net effect of our capital market assumption amendments

This exercise caused us to realize that despite our rigorous testing, the method used to build capital market assumptions may need to be adjusted between macro classes (for example fixed income and domestic equities) and the method used not only needed to pass all of our previous tests, but also, needed to minimize errors *throughout* <u>*and*</u> *across* all asset class components of macro asset classes.

A sound method of building assumptions should not be materially impacted by a few observations, even severe ones like 2008. Assumptions that do not model events like 2008 are either bad assumptions, or poor modeling.

For large cap stocks, adding all of the market data from 2001 through 2008 to the original data set we used to build our previous assumptions (and applying our previous methodology of taking the average of all ten year returns) would have reduced the mean return assumption from 12.32% to 12.17%, a reduction of 15 basis points. The standard deviation, again based on the average of 10 year standard deviations would have increased from 18.38% to 18.51%, a difference of 13 basis points. Our original assumptions had the median simulated 30 year return 51 basis points higher than the median historical period, but at the 75th percentile (where we begin measuring confidence) 106 basis points lower than the 75th percentile of history. Our new assumptions, in switching the return assumption to the median ten year return (instead of the average to correct for how skewed small and micro cap returns were) show the median simulated 30 year return as 45 basis points higher than the historical median (6 basis points less than the previous method and data) and the 75th percentile returns as being 104 basis points lower (versus 106). The new method shows similar differences for our new asset class assumptions for total domestic equities (see Chart 4).

Chart 4- New capital market assumptions simulated 30 year compound return distribution difference from 637 historical compound returns for domestic equities and large cap stocks.



Total Domestic Equities:

	Max	10% -tile	25% -tile	33% -tile	50% -tile	66% -tile	75% -tile	90% -tile	Min
History	14.5	13.0	12.4	11.9	10.9	10.4	10.2	9.6	7.6
Simulated	24.6	16.0	13.9	13.0	11.4	9.9	9.1	7.2	0.6
Difference	10.1	3.0	1.5	1.1	0.5	-0.5	-1.1	-2.4	-6.9

Large Cap Stocks:

	Max	10% -tile	25% -tile	33% -tile	50% -tile	66% -tile	75% -tile	90% -tile	Min
History	14.2	12.7	12.0	11.6	10.4	9.9	9.7	9.1	7.2
Simulated	23.5	15.2	13.2	12.4	10.8	9.4	8.6	6.8	0.5
Difference	9.2	2.6	1.2	0.8	0.5	-0.5	-1.0	-2.3	-6.8

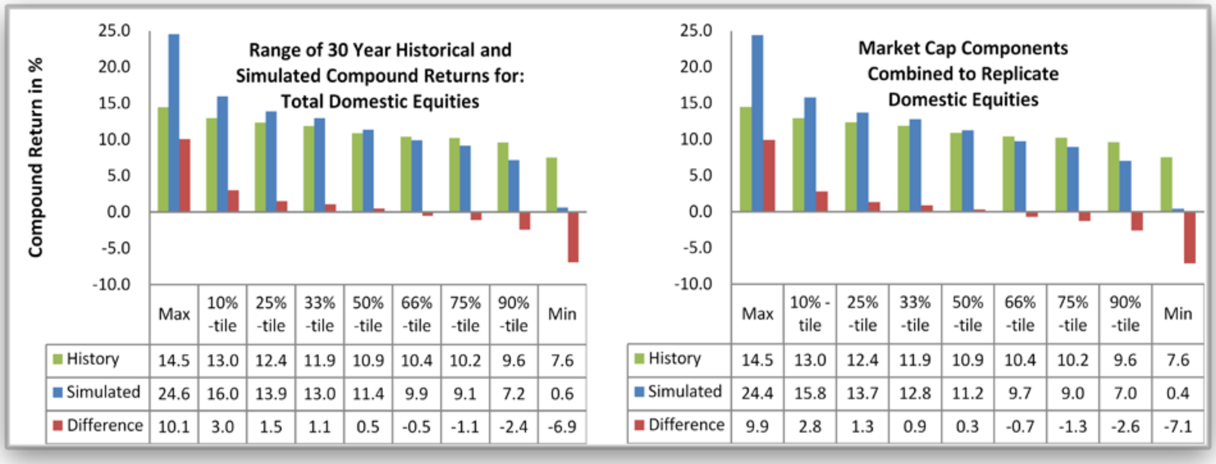
This wider range of outcomes is what one would expect considering we are simulating 30,000 independent years versus 82 years of independent historical data in the form of 637 thirty year periods constructed from monthly data. But by changing to the median ten year return for our smoothing assumption, we were able to correct for previous errors for small and micro cap without impacting mid cap, large cap, or total domestic equities in any material way.

There are more green $wans than black ones.

When one looks at the shape of distributions of historical returns for small and micro cap stocks, we observe that it does not fit very well into a normal or log normal distribution. **The best 12 month period for small caps was an amazing 344% and for micro caps it was 567%,** both occurring for the one year ending June of 1933. In a normal distribution, these represent more than +10 standard deviation events of observing profitable green swans. Between both small and micro cap there was only one observation of a -3 standard deviation event. If you are hunting for swans it is much easier to find green ones than black ones in the historical data. In a log normal distribution (which compensates for not being able to lose more than 100% in any year) small and micro cap stocks have a statistically significant number of either +3 or +4 standard deviation one year observations with only one -3 standard deviation event observed between them (which by the way is the exact number a log normal distribution would predict from the 1,970 observations). So our log normal shape matches what would be expected from extreme negative shocks, but slightly under predicts the number of extreme positive observations. But these extreme positive events are what cause simple averages (or even our prior smoothing method) to produce skewed results. Now, with our improved method, if one attempts to recreate domestic equities by using the average weights of its market cap components, they add up within an acceptable statistical margin of error of only 3 basis points difference in standard deviation and 17 basis points in geometric mean return. By finding a new method that worked for macro classes and *across sub class components* that also compensated for skewed data in some sub classes, we now have a method that permits the pieces to add up to the whole. Observe that in *Chart 5*,

<u>throughout</u> the entire probability distribution, the *difference* from historical returns to simulated returns is within 20 basis points of one another regardless of whether we use our new assumptions for domestic equities overall, or we use the assumptions for the market cap components assembled to equal their average weights within domestic equities. This equates to a margin of error in the confidence level of a little less than 2 points[3], well within our comfort zone.

Chart 5- Range of simulated outcomes to history for total domestic equities, and total domestic equities based on simulations created from the market cap level assumption components.



	Max	10% -tile	25% -tile	33% -tile	50% -tile	66% -tile	75% -tile	90% -tile	Min
History	14.5	13.0	12.4	11.9	10.9	10.4	10.2	9.6	7.6
Simulated	24.6	16.0	13.9	13.0	11.4	9.9	9.1	7.2	0.6
Difference	10.1	3.0	1.5	1.1	0.5	-0.5	-1.1	-2.4	-6.9

	Max	10% - tile	25% -tile	33% -tile	50% -tile	66% -tile	75% -tile	90% -tile	Min
History	14.5	13.0	12.4	11.9	10.9	10.4	10.2	9.6	7.6
Simulated	24.4	15.8	13.7	12.8	11.2	9.7	9.0	7.0	0.4
Difference	9.9	2.8	1.3	0.9	0.3	-0.7	-1.3	-2.6	-7.1

Do you have fashion sense?

Having tackled domestic equities and the market cap components thereof, we moved on to evaluating our style assumptions. Here again, while our previous assumptions passed all of our previous tests and would be selected for use by a mean variance optimizer, the parts did not add up to the whole. Of course, we don't really consider styles to be an asset class per se, but merely instead represent a non- diversified piece of the whole market. Data availability from vendors for which we can license and redistribute style data back to 1926 is non-existent, yet the Fama/French data library[4] is available for us to at least test the assumptions we build.

We look at the choice of style assumptions as carving the total domestic market into non-diversified pieces in much the same way we view market cap pieces of the market whole — the assumptions need to add up to the whole and data can be skewed. For example, when it comes to market cap level assumptions, we are comfortable with the notion that small cap stocks have higher standard deviations than large cap stocks. In 92% of the 877 historical ten year periods, small cap had a higher standard deviation than large cap. Higher average returns, as we saw in the section on our market cap research, occurred far *less frequently* with only 75.4% of the ten year periods having higher returns for small caps but the *extent* of the higher returns of small caps was much greater. This is why simple averages were skewed. Likewise, we cannot help but wonder if

[3] For example, with domestic equities modeled at the 82nd percentile for thirty year compound returns, the 83rd percentile is 9 basis points less than the 82nd and the 84th percentile is 25 basis points less.
[4] Available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

any arbitrary line like market cap or style introduces skewed data observations merely by drawing the line. After all, when a small cap stock grows up to be a mid cap stock, that growth is recorded in the small cap data set and the stock's performance thereafter is excluded from the small cap data. Likewise, when a mid cap stock declines in value to be demoted to a small cap stock, those losses are recorded in the mid cap data set and then the stock is no longer counted as mid cap. If the stock bounces back past the arbitrary line between small and mid, the gains along the way get credited to small cap stocks. The same thing occurs in style components. In reality, all market cap and style measures are merely measuring an active strategy, albeit with simple rules. Those pieces must still add up to the market whole, no matter how or how many ways you slice it. This is one thing we do know for sure. The other thing we know is that every assumption we need to create introduces errors as we discussed earlier. The more inputs you have, the more likely you will introduce potentially material errors.

When it comes to style research, the Kenneth French data library exposes how easily some analysts that ignore its availability can be fooled by recent data from the popular index vendors. I've seen assumptions from major firms that assume a higher return *and* lower risk for value than growth, or the total market. The data doesn't show this, nor does French make such a claim. Much like the frequency of higher returns for small cap relative to large, value stocks (measured as the bottom three deciles by price/book for the information contained herein) have more standard deviation than domestic equities in 74% of the historical ten year periods back to 1926 where the data begins[5]. Value stocks have a higher standard deviation than growth stocks (top three deciles on price/book) in 63% of the observations. The theory behind much of the Fama/French work is that value has a higher return *and risk* relative to the market and growth stocks; and growth stocks have less standard deviation and lower returns than the market. The return data supporting this theory is compelling. For the ten year compound returns, growth is under the total market in 78% of all ten year periods and value is over the market in 89% of the ten year periods. So the data appears to support the Fama/French theory that value stocks have higher return *and risk*. The data does not appear however to support growth being less volatile than the market, which would support our notion that it represents a riskier non-diversified piece of the total market. While the average ten year standard deviation was about the same between growth and the total market, we observe that **growth had less standard deviation in only 41% of the ten year periods.**

Assumptions that have the pieces equaling the whole

Those pesky correlation coefficients and skewed data observations for pieces of the markets can make it difficult to assemble capital market assumptions that are consistent with the laws of math. But we did it! Without attempting to explain a cause for the higher standard deviation and return of value stocks, when used in combination with other market cap and style measures weighted to mimic the total market, our new assumptions add up to the market whole. Fama and French should be pleased that our new assumptions permit a value risk and return premium. We also, as their data supports, assume a lower return than the overall market (or the market cap component thereof) for growth stocks. The compound returns capture their assumed return premiums (and

[5] The French data library starts at July of 1926, while all of our other data sourced here begins in January 1926. For the style data published here, we populated the missing six months with CRSP total domestic equity data for both styles to keep the sample size and calculations the same.

penalties) as well. We could not however assume growth stocks would have any less volatility than the market as a whole when the average ten year standard deviation was nearly the same and they more frequently than not had more standard deviation. To avoid dispute, we accept that the lower returning and less diversified growth stocks are going to be no more or less risky than the diversified total market, since it is consistent with our rules for building equity assumptions and the data supported it on average.

What this means is that you will get statistically the same answer whether you mold a portfolio of large cap blend with mid and small cap growth and value. Or, if you mix mid cap blend with small and large cap growth and value. Or, any other way you can combine the 9X9 style box. In fact, so long as you have the weights proportionate to total domestic equities, no matter how you combine any of the 9X9 style boxes, statistically you will get the same answer (plus or minus 6 basis points of standard deviation and 9 basis points of return). This is an amazing mathematical feat when you consider the impact of imperfect correlation data and market cap weights shifting somewhat over time.

New assumptions pass old testing rules

It is important to remember that all of the tests from our original capital market assumption work still apply and those tests validate how the assumptions are being used in our wealth management platform. This enables skilled advisors to truly deliver Wealthcare to manage lifestyle choices, and wealth results.

Fixed Income, Foreign and Alternative Investments

While we were refining all of our other assumptions, we also reviewed our rules for all of the remaining asset classes. Having discovered that our previous smoothing method introduced some skewness in certain pieces of the market, we looked across fixed income durations and found the opposite effect for shorter maturities. The shape of fixed income distributions for durations of 5 years or less was showing that there were not enough tail observations being counted in the averaging method, so we switched to the one year standard deviations for shorter maturity government, municipal and corporate bonds, updated the return assumptions based on proxies we could manufacture out of longer term data[6], and while having no impact on total returns (just tax treatment within our simulation engine) we adjusted the yield assumptions to equal the geometric mean of the return and risk assumptions.

Foreign stocks and bonds, and alternative investments were handled in the same manner as before. The markets of 2008 demonstrated the uncertainty introduced by currency risk and the lack of supporting data for various alternative classes showed that track records (and scandals…think about Madoff representing 2.5% of the total market cap of alternative) are highly uncertain. Since we have insufficient data to support any assumption for these classes, we adjust the risk and return considering this uncertainty to compensate for their primary use as a

[6] For example, other than T-bills, 5 Year bonds and long governments, the fixed income data for other maturities does not start until 1941. The main thing we are modeling with fixed income is interest rate risk. Instead of excluding data prior to 1941 for all fixed income, we created proxies by blending available data into an approximately equal duration for the period from 1926 to 1941.

diversification tool based on their lower correlations. These assumptions still have a mean variance optimizer selecting these classes for this purpose, and unlike other assumptions that would have portfolios dominated by these asset classes (Yale comes to mind) the risk of asymmetric covariance is considered and the portfolio uncertainty increases as one makes large gambles on currency bets or alternative classes.

Finally, we have added TIPS to our list of asset classes and have come up with what we consider a reasonable guess as to how they might behave. We did not buy the theories that there was a free lunch from TIPS (nor that they were essentially the same as regular treasuries, they are not) because theory and supporting data are two completely different things. The purpose of fixed income in an allocation is to lower the overall risk of equity markets[7] particularly in "shock" environments. The flight to safety, while not always present and still uncertain, did not work out for TIPS (or any other fixed income asset class other than government bonds) in 2008. TIPS were flat to slightly down in 2008 while our core fixed income exposure of 7-10 treasury bonds (IEF) behaved as expected returning 18% in 2008. It will take many years for TIPS to make up that 1,800 basis point spread. And with the debt the government is putting on, they could very well pay off if the forecasts of inflation come true. But, no one knows how they would have behaved in the last market shock of this magnitude. Perhaps they would have performed the same with the deflationary environment of the Great Depression. But, we know treasuries grew 19.74% in value during the four year market decline of 68.5% from 1929 through 1932. They behaved similarly in this most recent and most similar environment. None of the other fixed income classes materially protected your total portfolio principal by producing positive returns — not even high quality municipals. Even in the less severe and inflationary environment of the 1973-1974 bear market, treasuries were up 4.3% when the market declined 40.2%. And, when the internet bubble burst in 2000 to 2002 with total domestic equities declining 37.9%, long treasuries were up 46.8%.

The aggregate effect and summary

When you have a method of building capital market assumptions and a modeling method designed around the assumption of continuous uncertainty, and if you apply rigorous testing to see if the assumptions model what you intended and anticipate shocks that other assumptions and methods ignore, you should not have to change your assumptions. Over the last seven years, we haven't had the need to do so. We did discover some small improvements we could make however and hopefully these new assumptions will remain as valid as our past assumptions.

The last part of testing these assumptions is to run what we call an application test. Here, instead of just looking at how *we* model portfolios, we take over 17,000 real wealth management plans added to our system by our advisor clients over the last six months that use our capital market assumptions. By looking at a before and after delta of all of the capital market assumption adjustments, we can expose if we missed anything or if an unexpected use of an asset class in an allocation causes a strange result. We can also see the aggregate impact to confidence levels.

[7] Remember that Brinson, Hood and Beebower showed that 90%+ of the variance of returns are explained by the allocation to simply stocks, bonds and cash, which means that less than 10% of the variance is explained by all of the other sub asset classes that we know will introduce errors in the assumptions at an exponential scale.

On average, across all plans and the hundreds of different allocations modeled, our new capital market assumptions will reduce the confidence level by 2.4%, barely a shift in the distribution and well within our comfort zone margin of error (the median is 2.1%). Of the more than 17,000 plans, 58% will be within +/- 3%, 86% will be within +/- 6% and 94% will be within +/- 8%, approximately the extremes of the comfort zone. The vast majority of those 6% of the plans that fall outside of this range were irrationally constructed portfolios that had excessive bets in the allocation to some of the classes we discovered needed modification. This is the price of making big bets.

In summary, the output from any model is only as good as the input. We are proud that we modeled and thus anticipated the most extreme markets that caught so many off guard. We are also proud that we did not permit ourselves to buy into financial mysticism that destroyed so much wealth last year and was sold based on hopes that that future data would prove the theory right. We prefer to trust data first and theories second, and if you do the same you can protect yourself from the litany of theories that have recently been proven wrong.

The probability distribution graphs for our model allocations based on the old and new assumptions follow along with the complete set of new capital market assumptions and correlation matrix.

A popular industry speaker and writer, DAVID B. LOEPER is the CEO and founder of Financeware, Inc. in Richmond, VA. He is author of the top selling book Stop the 401(k) Rip-off!, three other books being released in 2009 by John Wiley & Sons (Stop the Retirement Rip-off, Stop the Investing Rip-off and The Four Pillars of Retirement Plans) and numerous whitepapers. He has appeared on CNBC and Bloomberg TV, served on the Investment Advisory Committee of the $30 billion Virginia Retirement System, and was chairman of the Advisory Council for the Investment Management Consultants Association (IMCA). Before founding Financeware in 1999 he was Managing Director of Strategic Planning for Wheat First Union. He earned the CIMA® designation (Certified Investment Management Analyst) from Wharton Business School in 1990 in conjunction with IMCA.

Charts 6 through 11: Thirty year probability distributions for Wealthcare Capital Management's six allocation models based on our 2009 capital market assumptions compared to our 2001 assumptions.

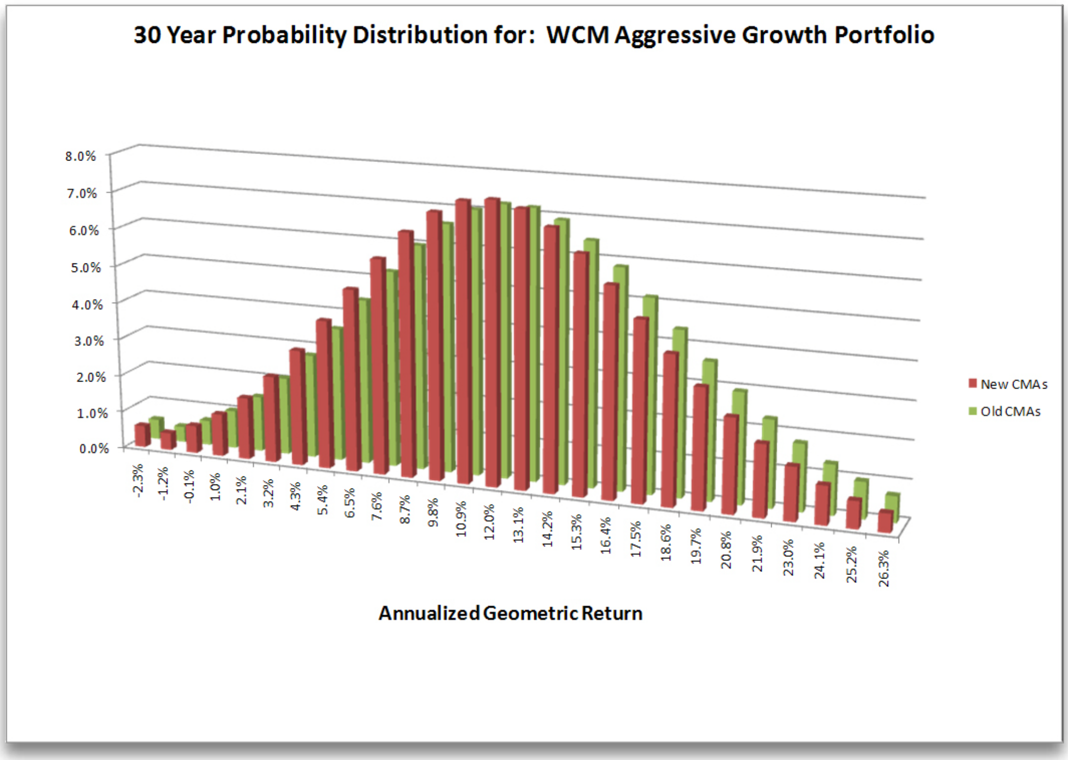


Chart 7- Growth Allocation

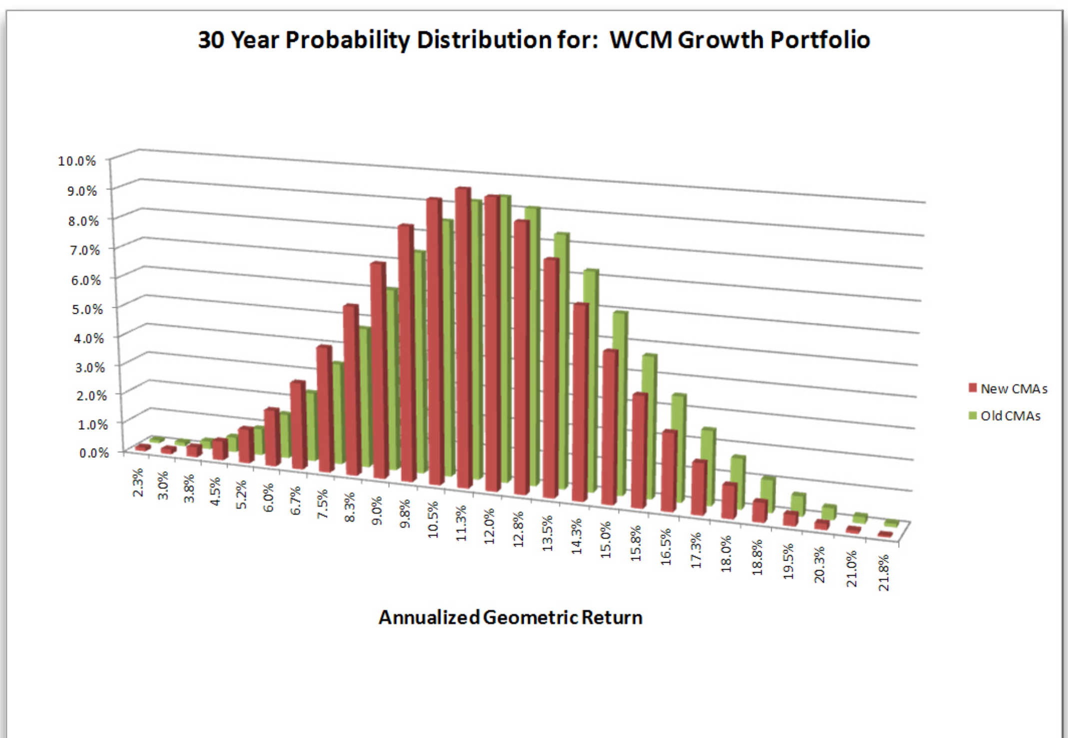


Chart 8- Balanced Growth Allocation

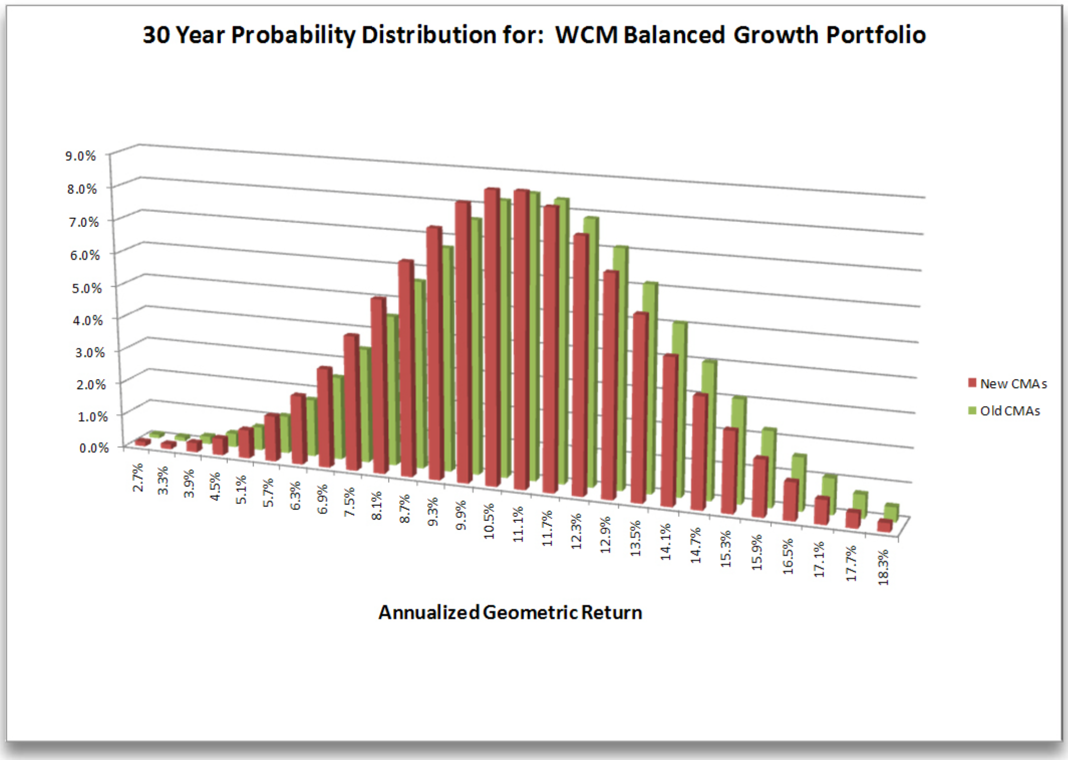


Chart 9- Balanced Allocation

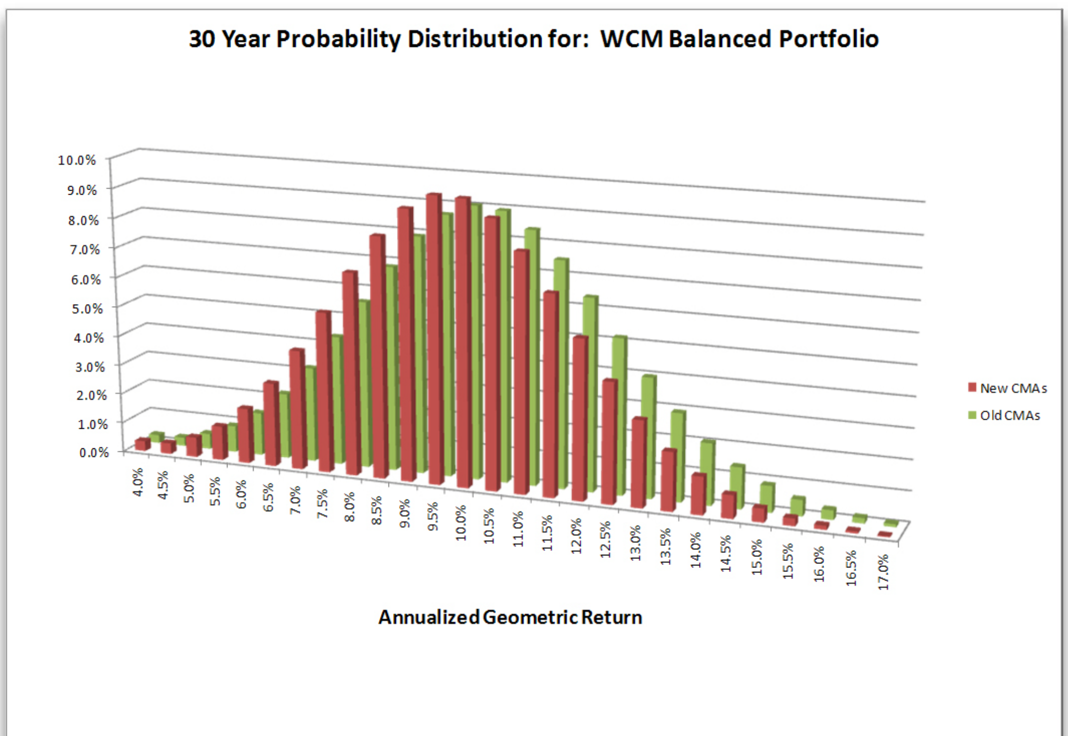


Chart 10- Balanced Income Allocation

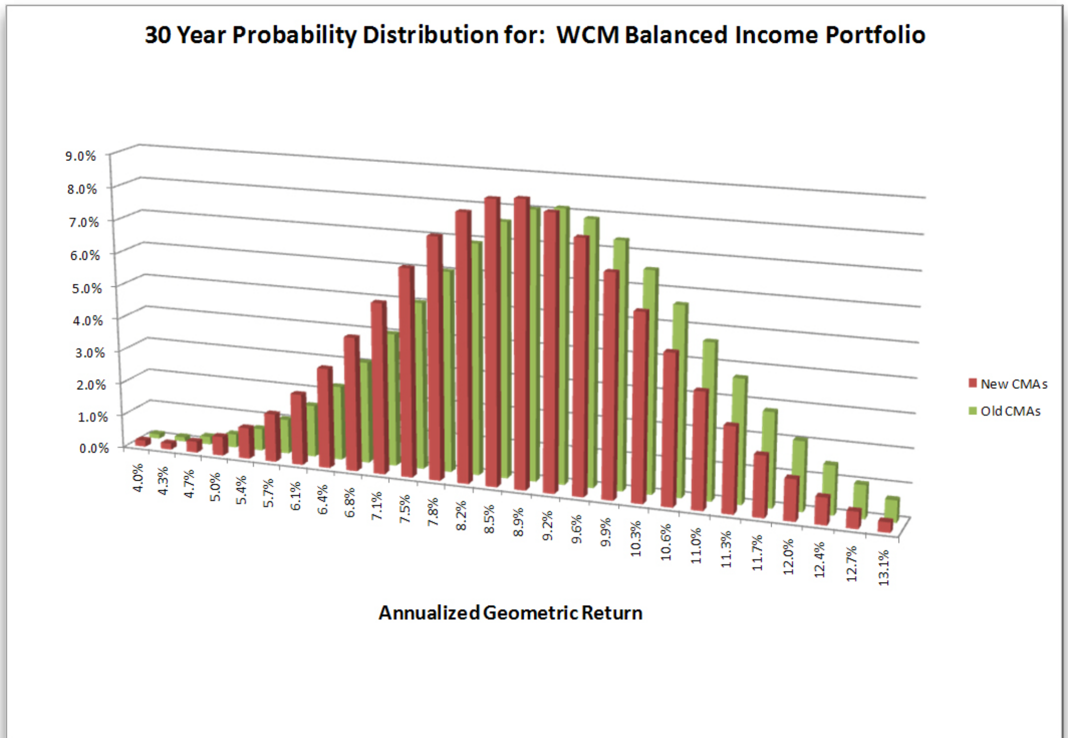


Chart 11- Risk Averse Allocation

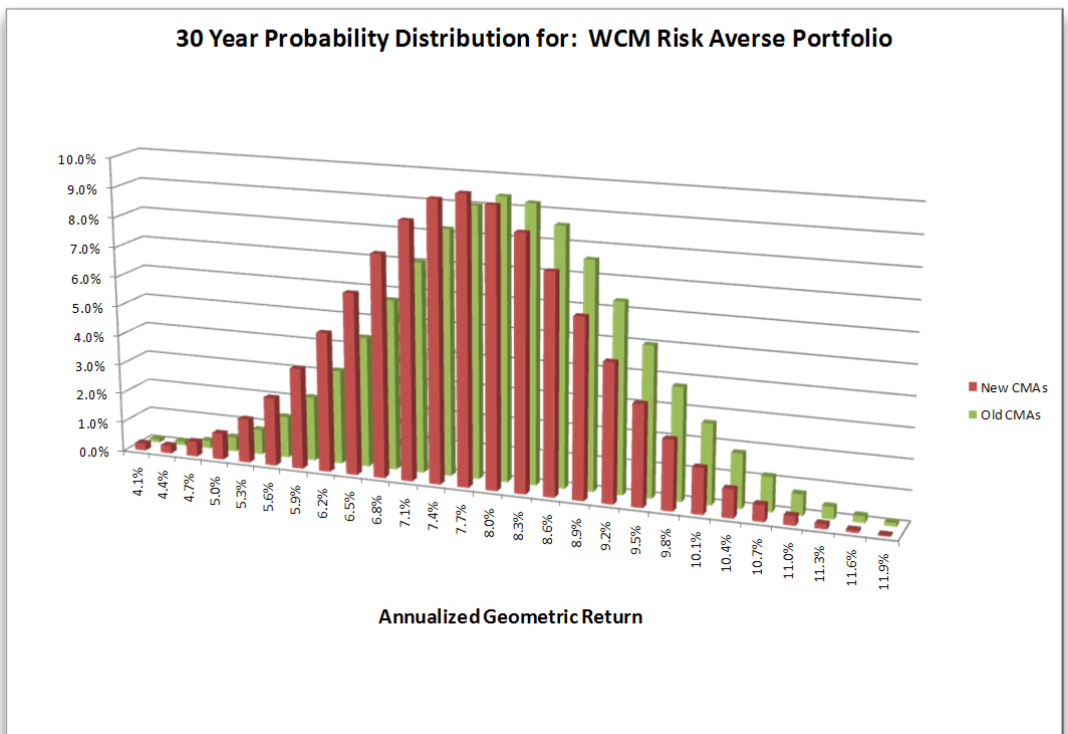


Table of Capital Market Return, Risk, Yield and Correlations:

Class Name	Return	Risk	Yield	Yield Taxable	Geo- metric Median Return	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
1 Total Domestic Equity	13.2	19.3	4.05	Y	11.60	1.00																																	
2 Large Cap Diversified	12.5	18.51	4.13	Y	11.01	0.99	1.00																																
3 Large Cap Value	13.5	20.33	5.16	Y	11.72	0.91	0.92	1.00																															
4 Large Cap Growth	11.5	18.51	3.09	Y	9.99	0.97	0.97	0.82	1.00																														
5 Mid Cap Diversified	15	23.19	4.04	Y	12.76	0.95	0.91	0.85	0.90	1.00																													
6 Mid Cap Value	16	26.14	4.84	Y	13.19	0.89	0.86	0.96	0.78	0.89	1.00																												
7 Mid Cap Growth	14	23.19	3.23	Y	11.74	0.93	0.89	0.75	0.93	0.96	0.77	1.00																											
8 Small Cap Diversified	15.9	28.08	3.66	Y	12.65	0.88	0.82	0.75	0.83	0.96	0.80	0.92	1.00																										
9 Small Cap Value	16.9	30.18	4.39	Y	13.20	0.82	0.76	0.81	0.71	0.89	0.90	0.78	0.91	1.00																									
10 Small Cap Growth	14.9	28.08	2.92	Y	11.63	0.87	0.80	0.68	0.84	0.94	0.74	0.94	0.98	0.86	1.00																								
11 Micro Cap Stocks	17.2	37.03	2.51	Y	11.72	0.80	0.72	0.67	0.74	0.87	0.72	0.83	0.94	0.86	0.91	1.00																							
12 Gov't/Corp Bonds	5.57	5.48	5.43	Y	5.43	0.14	0.17	0.18	0.14	0.10	0.17	0.08	0.04	0.07	0.01	-0.01	1.00																						
13 Intermediate Gov't Bonds (7-10 Yr)	5.67	6.68	5.46	Y	5.46	-0.06	-0.02	-0.03	-0.05	-0.11	-0.04	-0.11	-0.16	-0.13	-0.17	-0.20	0.92	1.00																					
14 Long Term Gov''t/Corp	5.99	8.9	5.62	Y	5.62	0.15	0.17	0.17	0.14	0.12	0.19	0.11	0.06	0.09	0.04	0.02	0.95	0.83	1.00																				
15 Long Term Gov''t Bonds	5.82	7.48	5.56	Y	5.56	0.04	0.06	0.06	0.04	0.00	0.07	0.00	-0.05	-0.02	-0.06	-0.09	0.93	0.88	0.96	1.00																			
16 Short Term Corp. Bonds	5.05	4.01	4.97	Y	4.97	0.19	0.20	0.21	0.18	0.18	0.22	0.15	0.11	0.11	0.08	0.09	0.77	0.66	0.71	0.60	1.00																		
17 Short Term Gov''t Bonds	4.92	3.85	4.85	Y	4.85	-0.08	-0.04	-0.06	-0.06	-0.14	-0.09	-0.14	-0.19	-0.18	-0.20	-0.22	0.83	0.93	0.67	0.73	0.65	1.00																	
18 High Yield Bonds	7.24	10.98	6.68	Y	6.68	0.59	0.56	0.57	0.54	0.63	0.63	0.57	0.62	0.64	0.57	0.65	0.28	0.02	0.31	0.13	0.42	-0.03	1.00																
19 Foreign Bonds	6.08	12.48	5.35	Y	5.35	-0.04	-0.03	-0.04	-0.03	-0.05	-0.04	-0.04	-0.07	-0.10	-0.06	-0.12	0.40	0.43	0.37	0.37	0.33	0.38	0.04	1.00															
20 TIPS	5.93	8.9	5.56	Y	5.56	0.16	0.18	0.20	0.16	0.12	0.2157	0.11	0.06	0.10	0.03	0.02	0.90	0.80	0.88	0.88	0.68	0.70	0.29	0.36	1.00														
21 10 Year Municipal Bonds	4.41	6.68	4.2	N	4.20	0.19	0.20	0.23	0.16	0.16	0.24	0.13	0.10	0.15	0.07	0.08	0.76	0.68	0.72	0.68	0.59	0.58	0.30	0.27	0.65	1.00													
22 Long Term Municpal Bonds	4.48	7.47	4.22	N	4.21	0.27	0.29	0.32	0.24	0.26	0.35	0.21	0.18	0.23	0.14	0.14	0.70	0.55	0.67	0.59	0.59	0.46	0.39	0.21	0.62	0.93	1.00												
23 Intermediate Municipal Bonds	4.35	5.2	4.22	N	4.22	0.13	0.14	0.16	0.10	0.10	0.17	0.07	0.05	0.09	0.03	0.04	0.77	0.72	0.71	0.68	0.60	0.65	0.25	0.32	0.65	0.96	0.85	1.00											
24 Short Term Muncipal Bonds	3.78	3.85	3.71	N	3.71	-0.08	-0.04	-0.06	-0.06	-0.14	-0.09	-0.14	-0.19	-0.18	-0.20	-0.22	0.83	0.93	0.67	0.73	0.65	**1.00**	-0.03	0.38	0.70	0.58	0.46	0.65	1.00										
25 Tax Free Money Market	3.21	3.4	3.21	N	3.15	0.08	0.10	0.07	0.10	0.03	0.03	0.05	0.00	-0.01	0.02	-0.06	0.14	0.13	0.04	0.05	0.20	0.30	-0.02	0.01	0.09	0.09	0.10	0.11	0.30	1.00									
26 90 Day T-Bill	4.27	3.4	4.27	Y	4.21	0.06	0.09	0.06	0.09	0.01	0.00	0.03	-0.03	-0.06	-0.02	-0.07	0.23	0.22	0.11	0.11	0.36	0.41	0.02	0.06	0.19	0.14	0.15	0.17	0.41	0.93	1.00								
27 Other/ Undefined	4.33	37.03	1.46	Y	-1.68	0.64	0.61	0.58	0.60	0.66	0.58	0.63	0.65	0.60	0.64	0.64	-0.06	-0.21	-0.03	-0.15	0.10	-0.22	0.48	-0.05	-0.07	-0.06	0.03	-0.08	-0.22	0.00	-0.02	1.00							
28 Emerging Markets	16.4	30.95	2.51	Y	12.44	0.64	0.61	0.58	0.60	0.66	0.58	0.63	0.65	0.60	0.64	0.64	-0.06	-0.21	-0.03	-0.15	0.10	-0.22	0.48	-0.05	-0.07	-0.06	0.03	-0.08	-0.22	0.00	-0.02	1.00	1.00						
29 Foreign Stock	12.5	24.06	4.13	Y	10.01	0.64	0.63	0.60	0.61	0.63	0.58	0.59	0.57	0.53	0.56	0.50	0.11	-0.04	0.12	0.03	0.19	-0.08	0.46	0.39	0.13	0.10	0.19	0.06	-0.08	0.01	0.02	0.60	0.60	1.00					
30 Managed Futures	5.5	28.91	0	Y	1.75	-0.18	-0.18	-0.19	-0.17	-0.17	-0.18	-0.16	-0.18	-0.18	-0.16	-0.21	0.13	0.17	0.13	0.19	0.03	0.16	-0.19	0.04	0.14	0.04	0.01	0.05	0.16	0.13	0.12	-0.17	-0.17	-0.11	1.00				
31 Concentrated Large Cap	12.5	55.53	4.54	Y	0.88	0.64	0.61	0.58	0.60	0.66	0.58	0.63	0.65	0.60	0.64	0.64	-0.06	-0.21	-0.03	-0.15	0.10	-0.22	0.48	-0.05	-0.07	-0.06	0.03	-0.08	-0.22	0.00	-0.02	**1.00**	**1.00**	0.60	-0.17	1.00			
32 Concentrated Small Cap	15.9	84.24	3.54	Y	-6.24	0.64	0.61	0.58	0.60	0.66	0.58	0.63	0.65	0.60	0.64	0.64	-0.06	-0.21	-0.03	-0.15	0.10	-0.22	0.48	-0.05	-0.07	-0.06	0.03	-0.08	-0.22	0.00	-0.02	**1.00**	**1.00**	0.60	-0.17	**1.00**	1.00		
33 Hedge Funds	5.5	28.91	1.5	Y	1.75	-0.18	-0.18	-0.19	-0.17	-0.17	-0.18	-0.16	-0.18	-0.18	-0.16	-0.21	0.13	0.17	0.13	0.19	0.03	0.16	-0.19	0.04	0.14	0.04	0.01	0.05	0.16	0.13	0.12	-0.17	-0.17	-0.11	**1.00**	-0.17	-0.17	1.00	
34 Real Estate/ REITs	8.02	14.51	4.57	Y	7.06	0.51	0.47	0.58	0.41	0.56	0.68	0.45	0.58	0.72	0.51	0.57	0.18	0.00	0.20	0.07	0.23	-0.06	0.62	0.04	0.23	0.24	0.31	0.18	-0.06	-0.04	-0.05	0.39	0.39	0.37	-0.26	0.39	0.39	-0.26	1.00

