Practical experiences in financial markets using Bayesian forecasting systems

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Introduction & summary

This report is titled “Practical experiences in financial markets using Bayesian forecasting systems”. The presentation is in a discussion format and provides a summary of some of the lessons from 15 years of Wall Street experience developing and using Bayesian-based forecasting models to provide the inputs into mean-variance optimization systems to generate portfolios for investment. While on occasion, several of the team members that have worked on the systems examined in this report have written and published academic articles and books related to financial market analysis and Bayesian forecasting systems, this report in no way pretends to be a scholarly study of the subject. Our purpose is to provide a more informal tour through our work in Bayesian-based financial systems.

The first section of this informal report, “Choosing the toolkits” focuses on why we chose mean-variance optimization systems to build our portfolios and chose Bayesian-based forecasting systems to provide the required inputs to the portfolio construction system. Hence, our discussion starts with our choice of a portfolio construction system.

We spend a lot of time trying to understand how successful non-quantitative traders and portfolio managers think and invest. We also study financial markets to gain insights into the price discovery process. In this section, we try to bring together some of these ideas to shed light on why we believe Bayesian-based forecasting systems have so much potential in financial time series analysis when coupled with mean-variance optimization methods to construct portfolios.

The second section of the report, “Notes on our research philosophy in building dynamic Bayesian forecasting models”, focuses explicitly on some of the issues and challenges in using a Bayesian-based forecast system to provide the expectational inputs for a mean-variance optimization system.

The third section, “A Selection of simulated experiments with Bayesian models”, illustrates some of our research work. We just present some basic summary information to compare different models and to highlight some of the key points from our investing experiences. Because these simulations are so closely tied to the specific parameter settings and factor choices of two of our Bayesian models, these results do not provide any real tests of our ideas. They are included in the informal report, however, to show how our research is conducted and how it is linked to our actual portfolio management.
Before moving into the body of this report, a little bit of historical background may be useful.

A group in which several of us belonged started working with Bayesian-based financial forecasting models at the beginning of the 1990s. Actual investment programs began to be run on our Bayesian-based systems in 1992. During the course of the last 15 or so years, our careers wound through several major financial institutions, and in each case the systems and investing programs became larger and more sophisticated. A core group of a number of the professionals that have been consistently involved in the research, development, and investment programs over the years have now joined together to form EQA Partners, LP, which will run a suite of hedge funds using discretionary portfolio management which is integrated with a comprehensive Bayesian-based research program. This informal report builds on the Bayesian-based research conducted in the consulting company owned by Bluford H. Putnam, Bayesian Edge Technology & Solutions, Ltd., from 2000 through 2006. Globally, we can identify over $2 billion now invested in hedge funds using explicit Bayesian-based research programs, where Bayesian Edge is a consultant.

I. Choosing the toolkits

One of our guiding principles is to use quantitative techniques that combine good theory with practical experience. With respect to theory, we have chosen to use a variant of the Markowitz mean-variance approach to portfolio construction. We have adjusted the basic Markowitz model in several important ways to more closely align it to what we see as best practices among highly successful, non-quantitative, portfolio managers. Thus, our portfolio optimization system contains a quantitative interpretation of some of the concepts that experienced portfolio managers hold dear to their hearts.

Here are some of the concepts that fall into the “best practices” category as seen by traders.

**Dispassion.** The only thing that matters is what is going to take place not what should, nor what you want. The market may be dancing to a different drummer, but it is never, by definition, “wrong”.

**Curiosity.** Curiosity cannot be taught. You need to be able and want to search for ideas and find the markets interesting. The best trades are not always the most obvious or commonly taken.

**Intuitively understand game theory.** Bets must be “sized” according to opportunity and liquidity. Press a bet when appropriate, cut losses when the idea is not working based on the plan. Again, no mere wishful thinking. Be resolute enough to jump on an idea quickly to better the chances of a positive result rather than miss the good ones.
**Ability to make logical connections.** Do not ask or care what other people think but file away all sorts of information; political, economic, social, weather, to get a world view.

**Do not be sloppy.** Simple mistakes should not happen and simple tasks should not slow you down. No extra effort should be needed to function, so mistakes are sensed and corrected quickly.

**Luck.** Unfortunately luck also counts.

From the portfolio manager perspective, we can add a few more items to our "best practices" list.

**Focus on Themes.** One must understand what the portfolio is really doing. What are the themes and factors that lie beneath the actual exposures taken in the portfolio. One has to separate the wheat from the chaff and realize that a lot of trades may merely be expressing only one or two different themes. Different themes diversify the portfolio not different exposures.

**Understand what you do not know.** Focus on recognizing the nature of the information that is available versus the unknown information that could be critical for the portfolio. Having a sense of what one does not know helps greatly in maintaining a balance between fear and greed in a portfolio.

**Recognize the difference in portfolio management and trading.** A robust portfolio will have bad trades. Only one with perfect foresight can make perfect trades, and if we had perfect foresight we would not need a portfolio to control risk.

**Pay attention to noise.** When the signals one uses to build a portfolio provide little new information and there is a lot of noise, then it is time to take some risk off the table. One has to have the guts to say I do not know and be willing to adjust the portfolio accordingly. This is just as important as knowing when "the stars are aligned".

**From “best practices” to a quantitative approach**

We chose the Markowitz mean-variance methodology to build portfolios because we thought it fit well with the characteristics of successful portfolio managers. But we also know that it comes with a heavy burdens of assumptions to which one must pay close attention.

By their nature, quantitative systems are dispassionate, but can they be curious? Well, they are not exactly curious, but they are thorough. Because of the key role played by correlations between each pair of security returns in the optimization process, the quantitative system can dispassionately look through all combinations of exposures with which to construct a portfolio without getting sidetracked or losing focus. For the
portfolio manager, such an optimization process can often unearth ways to express themes that were not at all obvious at first glance.

A quantitative portfolio system can only make the logical connections for which it is programmed. The leap of faith is that the relationships among expectations about returns, volatility, and correlations, are the proper logical connections to explore. The emphasis of successful portfolio managers are recognizing themes, separating signals from noise, and understanding what they know and do not know have reinforced our own view that back in the 1950s Markowitz had distilled the essence of the key logical connections required to build superior risk-adjusted portfolios.

Finally, we note that programming and data input errors can be just as deadly to portfolio returns as human errors. We build into our systems various filters and checks to help us eliminate errors. The best filter, however, is mean-variance optimization itself. The common term from the computer world, “GIGO”, for garbage-in, garbage-out, does not do mean-variance optimization methods justice. A mean-variance optimization system is a garbage maximization system. A little bit of garbage in, and you get a landfill of trash coming out of the system. That is, errors tend to get compounded and the resulting portfolios are so extreme that one immediately knows to look for data input errors.

Having chosen the Markowitz mean-variance optimization system as our toolkit for constructing research portfolios, one still has many, many decisions to make in configuring the system so that it will follow the guiding concepts of successful portfolio managers in the subtleties as well as the big picture.

We will now go through our interpretation of how to use a mean-variance optimization system in practice.

Choice of securities. For the effective use of a mean-variance optimization system, one must realize that the system is assuming that the future excess returns of each security are normally distributed. We are continually evaluating the robustness of this assumption, since few securities, if any, display even approximately normal distributions in the historical data, regardless of the time frequency chosen for the study. Nevertheless, certain types of securities are likely to be more prone than others to display a normally distributed pattern of excess returns going forward.

Our view is that securities that are considered liquid in both up and down market environments are much more likely to produce excess returns that conform more closely to the normal distribution. Thus, we have focused our portfolios only on the more liquid markets.

From the currency markets, we have chosen to consider the major exchange rates, as well as a few minor ones. Liquidity can be an issue for some of these currencies, and we will discuss that later in this report.
From the bond markets, we focus only on the larger countries, and only on the benchmark bonds.

From the equity markets, we focus only a select few equity indices that trade broadly.

And from the commodity markets, the list is short, indeed, with only three commodities and one composite (index) currently on our trading list.

For reasons we will discuss later, we also include in our systems a number of less liquid securities we do not plan to trade. As we will see later, we believe that there is an informational advantage to having these securities in our systems, even though we currently do not use them.

**Potentially traded securities**

Currencies in the Global Macro Portfolio:

- USD – US dollar
- EUR – Euro
- JPY – Japanese yen
- GBP – British pound
- CHF – Swiss franc
- AUD – Australian dollar
- CAD – Canadian dollar

Currencies in the Currency-Only Portfolio:

- USD – US dollar
- EUR – Euro
- JPY – Japanese yen
- GBP – British pound
- CHF – Swiss franc
- AUD – Australian dollar
- CAD – Canadian dollar

Plus, we add some less liquid currencies to this portfolio, including:

- SEK – Swedish krona
- NOK – Norwegian krone
- NZD – New Zealand dollar
- MXN – Mexican peso
- KRW – Korean won
Government bonds markets potentially used in the Global Macro portfolio:

United States
Germany
Great Britain
Japan

Government bonds markets in the system but not currently used in the portfolio:

Canada
Australia
New Zealand
Mexico
Korea
Switzerland
Sweden
Norway

Equity market indices currently potentially used in the portfolio:

United States
Europe-wide index
Great Britain
Japan

Equity market indices currently not used in the portfolio, but included in the system:

Canada
Australia
New Zealand
Mexico
Korea
Switzerland
Sweden
Norway
Germany
France
Italy
Spain
Emerging Markets Equity Index
Commodities currently potentially used in the system:

CRB (Commodity Research Bureau Index)
Crude oil
Gold
Copper

Commodities that are not used in the portfolio, but included in the system:

Natural gas
Gasoline (refined)
Platinum
Silver
Corn
Wheat
Soybean
Sugar
Cattle

At the portfolio research level, we do not use options and we do not use securities with embedded options, such as mortgages or structured notes. In short, our choice of securities to include in the research version of the Global Macro portfolio is focused on seven currencies (includes our numeraire, the US dollar), four government bond markets, four equity indices, and four commodities (one composite index, one energy sector commodity, and two metals).

In addition to the government bond markets and equity indices that are allowed inside the research portfolio, we also consider in our systems the bond and equity markets of major and minor currencies, and a variety of energy, metal, and agricultural commodities.

Our choice of securities that are potentially included in our portfolios maximizes our liquidity as well as giving us a reasonable degree of confidence that the embedded assumption that future security returns will be normally distributed is a worthwhile simplifying assumption.

Developing the portfolio objective

While choosing the securities to be included in the portfolio is a critical task, the criteria by which various possible portfolios are evaluated for selection is just as important.

In an optimization approach, the chosen portfolio is the one that produces the maximum value for a specific objective function of all the possible portfolios considered. In the basic Markowitz mean-variance optimization system, the objective function to be maximized is a simple quadratic equation that focuses on the trade-off between
expected return (mean) and expected volatility (variance or square of the standard deviation).

In talking to portfolio managers about the characteristics they prefer to see in portfolios, we have found that a few additions to the trade-off between expected return and expected volatility are often desired. In particular, we add some additional "penalties", for various measures of portfolio characteristics, including

Trading costs,
Concentration,
Leverage, and
Liquidity.

In words, the objective function expresses a positive goal of achieving the highest possible expected return adjusted for a set of penalties depending on the degree of:

expected volatility,
trading costs,
concentration,
leverage,
and expected liquidity.

The measurement indexes for trading costs, position concentration, and liquidity are constructed in a quadratic form to increasingly emphasize larger assessments in a non-linear manner.

Our portfolio construction system allows us to set the specific parameter value for each penalty. Setting the parameter value to zero eliminates the penalty from consideration in choosing the portfolio. In practice, the risk aversion penalty for expected volatility does the heavy lifting. We sometimes set the other penalty aversion parameters to zero or very low values so that they will move the portfolio to another choice only if the return to volatility trade-off is only effected in a small way.

In general, we first test all our research models with only a positive risk aversion parameter and zero settings for all other parameters. We want to make certain that the basic system produces reasonable portfolios before adding any additional penalties.

We also do not use boundary value constraints, other than to eliminate completely securities we do not wish to include in the portfolio. For example, boundary value constraints are of the form that one cannot have leverage more than 3 to 1, or one cannot have more than 25% of the portfolio in any one security, that transaction costs can never exceed some specific threshold, or that expected volatility is capped at 12%.

To our view, boundary value constraints violate the basic idea behind our optimization criteria. Portfolios are always a set of trade-offs. Penalties allow for incremental adjustments. Moreover, from a mathematical perspective boundaries present much
more complex problems for finding optimal solutions. While these issues are effectively handled with iterative solution algorithms, which we use, we still prefer to avoid putting our portfolios in a straight-jacket of constraints, so to speak.

When one puts a crazy man in a straight-jacket, the bad behavior is controlled, but the cause is left untreated. In unconstrained optimization, bad behavior (in the simulated returns of portfolios or in the characteristics of the portfolios) is readily identified and then becomes a challenge for the research team to eliminate the problem at its root. In the end, we want to know that our systems can produce reasonable portfolios with attractive risk-adjusted returns in simulation mode without resort to boundary-type constraints. Otherwise, we will never know if the resulting performance is due to the constraints or the inherent robustness of the system we have built.

In the end, our portfolios are chosen through a non-linear, iterative process in which the objective function to be maximized reads like this (in words):

Objective =

\[
\text{Expected Portfolio Return} - \text{Expected Portfolio Variance times Volatility Aversion Parameter (Lambda)} - \text{Measure of Portfolio Transaction Costs times Trading Costs Aversion Parameter (Delta)} - \text{Measure of Portfolio Size Concentration times Concentration Aversion Parameter (Gamma)} - \text{Measure of FX Leverage times FX Leverage Aversion Parameter} - \text{Measure of Liquidity times Liquidity Aversion Parameter}.
\]
Transaction costs, liquidity measures, and variance adjustments

The mean-variance method requires a set of inputs for each security, namely an expected return, an expected variance, and an expected correlation matrix for all the pairs of security returns. These estimated inputs come from our dynamic Bayesian forecasting system, discussed shortly. For now, it is important to note, that several other security specific inputs are used in the optimization process.

Transaction costs are estimated for each security. We have the ability, although we rarely use it in practice, to change the transaction costs for different periods of time. For example, one might want to increase transaction costs around holidays, especially at the end of each calendar year.

The liquidity penalty embedded in the optimization system is based on a portfolio liquidity measurement, which in turn depends on the liquidity index assigned to each security. Markets that are considered reasonably liquid, for their asset class, in fair or foul weather, are assigned a zero. The higher the number, the less liquid in foul weather (i.e., down markets). For example, in the currency world, we tend to assign measures indicating less liquidity to the Mexican peso, Korean won, New Zealand dollar, Swedish krona, and Norwegian krone. Remember, though, that these liquidity assessments come into play only if the liquidity aversion parameter is non-zero. We first try to build a forecasting system where liquidity issues are reflected in return forecasts and/or volatility forecasts, and extra penalties are not needed.

We also have built into our system the ability to adjust the volatility forecast higher if we feel the forecasted input for expected volatility is not doing a good job. Currently, we are not using this feature of our system. Nevertheless, it could be used during some future period in which we felt a certain degree of optionality had become embedded in a market, even if only for a short time. This can occur, for example, when a central bank targets an exchange rate or a short-term interest rate that is inconsistent with economic fundamentals. If enough market participants feel there is a one-way bet, the likely future distribution of returns is not going to be normally-distributed until after the conflict between policy and market fundamentals is resolved.

We are now ready to turn to a discussion of the forecasted inputs from our Bayesian models – excess returns, volatility, and correlations.

Forecasting returns, volatilities, and correlations

Just as in the choice of the toolkit for building the portfolios, we also pay close attention to the interaction of theory and practice in the choice of our toolkit for developing the forecasts required by our portfolio construction process. In our case, mean-variance optimization theory tells us that what is required are forward-looking views for security
excess returns, volatility, and correlations between all the pairs of expected security excess returns.

Our discussions with successful traders and portfolio managers has emphasized several notable items.

**Market drivers come and go.** Under certain market environments, traders and portfolio managers seem to focus on just a few key factors that appear to be driving markets. Over time, however, these key drivers change, and new drivers appear. Moreover, even if a key driver remains in the mix, its relative importance may evolve and its impact can even change in nature or direction.

**Markets are inter-related.** What is happening in commodity markets can influence inflation expectations and bonds, as well as profit forecasts and equities. Central bank driven changes in short-term interest rates can impact currencies one way and bonds another. A market disturbance in one sector can be contagious, spreading soon to other sectors or asset classes.

**Recent information is more valuable than old information.** For market participants, the new information is critical and the old information is already incorporated into the market price. Moreover, surprises count for a lot more than confirmation of the expected. Although one should not fall into the trap of thinking the confirmation of an expected event does not matter, as it effects confidence and market risk assessments, if not expectations of future events.

We agree with these market assessments by successful traders and portfolio managers. We have sought a quantitative forecasting toolkit that embraces these attributes rather than requires band-aides or a jury-rigging process to handle the problem.

For us, the choice of a system using Bayesian inference was a natural choice. Bayes' Theorem is about updating one’s expectations (mean) and confidence (variance) when new information is received. This is the essence of what good traders and portfolios managers succeed in doing so well – namely, process new information, updating their views and confidence assessments, and then creating new portfolios to reflect the revised expectations relative to their updated confidence in their views.

Moreover, the class of Bayesian systems applied to time series analysis has solved a number of issues that were problematic to more traditional approaches. Bayesian time series models embrace the nature of time-varying parameters. That is, the estimated coefficient that reflects the direction and magnitude of how a given factor effects market expectations of returns is considered a random variable that can dynamically evolve over time. This statistical interpretation of how market drivers evolve over time fits what successful traders and portfolio managers tell us about how markets behave. The concept of a fixed estimated factor coefficient that does not vary through time, as assumed in traditional regression analysis, makes no sense for financial markets.
Another statistical technique, seemingly unrelated regressions, as developed by Professor Arnold Zellner, also holds strong appeal. If we could specify exactly how markets are related to each other, we could build huge deterministic multi-equation models. This approach has been explored in detail, and a Nobel prize won for its development, but in the world of financial forecasting and real world portfolio management, the big, multi-equation deterministic models, have not done well.

By contrast, the seemingly unrelated regression approach argues that the information contained in how the errors in one’s forecasts of different securities are related is extremely important information, even if one does not know why the errors are related. In the Zellner approach, there is no requirement to do the impossible – explain exactly how the markets are related. All one needs to accept is that different markets are related and the that there is information in the correlation of the mistakes one makes in one’s forecasts.

In a Bayesian world, it is also a natural consequence that the value of information can vary with its age. The case where each piece of information, no matter how new or how old, has the same value is viewed in the Bayesian world as a unique case. The more general Bayesian system allows for new information to have more value than older information. Nevertheless, parameters can be set so that the traditional regression approach in which each piece of information has the exact same value regardless of age can be shown to be a special case contained within a generalized Bayesian framework for estimating time-varying parameters.

Finally, we like the Bayesian toolkit because it can accommodate expert information. In time series financial analyses, we never have enough data and must operate under some tough conditions, in terms of the robustness of our embedded assumptions. With data being scarce, expert information can have considerable value and allow one to jump-start a statistical process with a less than optimal quantities of data (from the point of view of a traditional statistician). One tool we use that incorporates expert information is Bayesian shrinkage. This is another technique developed by Professor Arnold Zellner, and it allows one to link the estimation process for factor coefficients when one has a good theoretical reason for such a process. In several of our models, the use of shrinkage is extremely important to the quality of our simulated results.

In the end, though, the Bayesian system we use looks a lot like traditional regression analysis on the surface. Do not let the similarity fool you, as the results from our Bayesian system differ markedly from what can be produced with traditional regression analysis. The incorporation of Bayesian inference in two critical places, as well as other non-Bayesian tools provides a much better quantitative match to the best practices of successful portfolio managers than a straightforward regression approach.

The two critical places where Bayes’ Theorem is used are (1) in the process of updating the estimates of factor coefficients, and (2) in the process of updating the expected covariance matrix, that is the revised forecasts of volatilities and correlations.
Think of a stack or set of estimation equations of the form:

\[
\text{Expected Return} = \\
\text{Bayesian Residual Momentum} \\
+ \\
\text{Estimated Coefficient #1 times Factor #1} \\
+ \\
\text{Estimated Coefficient #2 times Factor #2} \\
+ \\
\ldots \\
+ \\
\text{Estimated Coefficient #N times Factor #N} \\
+ \text{Forecasted Error Term}
\]

For every security in the system, whether used in the portfolios or not, there is an estimation equation.

Each time new data arrives, in our case every week, estimates of all of coefficients are revised, making use of Bayes’ Theorem and the seeming unrelated regressions approach in dynamic form. As part of the seemingly unrelated regression approach, the underlying estimated covariance matrix, containing the forecasts of volatilities and correlations is also revised using Bayes’ Theorem.

Bayesian shrinkage is used selectively for certain factors, for related securities, in certain types of models.

A parameter that controls the time decay of information is set separately for the estimation of factor coefficients and for the covariance matrix estimation and revising process. As a general rule, we always decay information faster (value more recent information more highly) for the Bayesian revision process involving volatilities and correlations relative to the revision process for estimated coefficients. This weights more recent information more heavily, allowing the model to adapt more quickly to correlation and volatility environments.
Obviously, in forecasting systems such as these, there is a lot of judgment. We choose the factors (i.e., yield curve, moving average cross over, etc.), we choose how the factors are expressed mathematically (percent change, binary signal, etc.), we choose the time periods under study (1995-present), we choose the time decay of information value (different speeds for different models, different speeds for factor coefficients versus volatilities and correlations), and we choose the periodicity of our data (i.e., tick, daily, weekly, monthly, etc.). There is plenty of research, quantitative and theoretical, involved in making all these choices. Inevitably, there is some data-mining, some hindsight, and some intuition.

What follows is a general discussion about how we make the judgments required to set the parameters, choose the factors, and generally develop Bayesian-based forecasting model that we think have a good chance of performing well, out of sample, in the real world of investing.

II. Notes on our research philosophy in building dynamic Bayesian forecasting models

There are a number of concepts and principles we use in our research process. What follows are a few concepts which we deem especially important.

Simulations can be too good!

In quantitative investment research, maximizing the information ratio typically reigns as the supreme objective. The information ratio is defined as the annual average excess return (over LIBOR) of the simulated portfolios divided by the annualized standard deviation of the excess returns.

In our experience, once one has done thousands or more simulations and also spent years investing real money in quantitatively developed portfolios, one comes to the understanding that simulated information ratios most definitely can be too good to be true. And while many researchers share this conclusion, there is no clear and systematic process for weeding out the “too good to be true” from the “this has long-term and robust investment potential”.

As our friend and Nobel laureate, Professor Harry Markowitz, has pointed out to us, no one wants to show your boss (or clients) your mediocre simulations, you show-off your simulations with the highest risk-return ratios (information ratios). Unfortunately, in this Markowitz world, by opting to implement only the simulation with very “best” result, one nearly guarantees that the actual results will be disappointing. Harry Markowitz, Gan Kin Xu, and Bluford Putnam have published an article on “Deflating research expectations” (Global Investor magazine, London, September 1996, and reprinted in the book, “Integrating Risk Management into Asset Allocation” by Bluford Putnam (ibid.).
Interested readers should also review “Death by Simulation”, by Bluford Putnam, published in “Integrating Risk Management into Asset Allocation”, London, Euromoney Institutional Investor, plc, 2000. This article explores several ways that researchers can create beautiful simulations that have little chance of making money in the real world.

One can probably do better than just deflating expectations of the simulation that is the “best” based on only one criterion (albeit an important criterion). One can apply some additional quantitative criteria (within the simulation research process) as well as some art in the selection of the investment process or model for actual implementation with real money.

Here are a few ideas, some quantitative and some artistic in nature, which we use to develop simulations that will work in practice to produce robust investment results, while sacrificing the beauty of some of our simulations that fell into the “too good to believe” category.

**What is too good?**

Really good investment professionals with long careers in financial markets generally produce information ratios in the 1.0 to 1.5 range, when the period under consideration is 10 years or longer. Higher ratios can occur in shorter time periods. While this does not mean we throw away our results when the information ratio exceeds, say 2.0, we do become much more cautious. Our own view is that once a simulated information ratio exceeds 1.5, then the gap between the simulation and the reality starts to widen very rapidly. We feel the same way about actual investment track records, in that track records with very high information ratios are more likely to reflect the special market circumstances of the period than any long-run ability to maintain such a high information ratio when the market structure and driving forces eventually change.

For example, after the Federal Reserve abruptly and sharply raised short-term interest rates in the spring of 1994, the mortgage-backed and asset-backed securities markets took a big tumble and the yield spread over US Treasuries got quite wide, even on “AAA” and “AA” credit securities that were in no danger whatsoever of default. They just lacked liquidity, and there was a lot of confusion surrounding the value of the embedded options often found in these structured securities. If you put on a portfolio of MBS and ABS exposures in the summer of 1994, you were going to make money for several years, regardless of your talent, given your fortuitous timing. Information ratios for MBS and ABS portfolio managers should have been at their highest level for the 1995-1997 period. Then, came the LTCM hedge fund debacle in the summer of 1998 to ruin the party for many (not all).

Another example was the “convergence trade” in the currency markets that preceded the introduction of the Euro. From 1995 through the end of 1998, when the Euro was actually introduced, being long the high-rate European currencies and being short the German mark allowed one to earn the carry. This trade worked spectacularly well, especially when leveraged, as it was by almost all currency traders. Currency track
records from the 1996-1998 period are often really good, with superior information ratios. The conditions that produced these high information ratios are also unlikely to be repeated in the future.

In the equity world, the bull market in stocks starting in the early 1990s, and running through 1999, was a wonderful opportunity for a rising tide to cover lots of investment process and risk control sins – until it abruptly ended in a meltdown that started in 2000. Everybody (his sister, her brother, their dog, their cat) thought they could pick stocks in the last few years of the 1990s.

Finally, the raging bull market in commodities, such as oil, gold, copper, etc, from 2003 through 2005, was a superb investment opportunity. Long-only commodity portfolios are going to produce some of the best information ratios for the 2003-2005 period. Like all superb opportunities, it came to an abrupt end in 2006, sending a few hedge funds to their fiery graves.

If one’s quantitative models latch on to these special opportunities, it can be a very good thing. In trying to understand research simulations, though, the art is in being able to figure out whether the model has been unintentionally optimized for these special periods at a cost of being able to adapt to the changes that are sure to come when the special opportunity meets its end.

In general, models that have a certain degree of robustness over long periods of time are never the best models for any given 3-5 year period. Usually, a specific theme tended to drive markets for shorter periods. Find the theme and bet the farm, and the track record can look very good – for a while.

Moreover, it is still possible to build a 10-year model that can be optimized for say, two or three themes, and still lack the robustness to handle the next new theme that catches the favor of the markets. It is truly an art to build a long-term robust quantitative model that will perform well out-of-sample and through several different types of market environments. And unfortunately, the prettiest simulated picture (of the information ratio) often leads to some not so pretty actual results. Yes, simulations can, indeed, be too good!

**What does one do when the simulated information ratio is “too high”?**

Well, first, let’s congratulate ourselves for achieving a very high information ratio in our research simulations, particularly if they cover a long period and involve more than one market environment. This is no small feat, even if we force ourselves to be skeptical of the robustness of the investment process when actually implemented. Then, we look for research trade-offs that can improve other qualities and characteristics of the investment process while giving up only a little of the “too high” simulated information ratio.
We look at the annual average returns, and see if we can understand the difficult periods and are able to tweak the model to eliminate or reduce the size of the loss in any “bad” years, by using techniques that we think may also help us in future years. Some “tweaks” may actually hurt future performance, so one has to be very careful at this step.

We look at the period in which the model had its largest (or longest) peak to trough to new peak period, and again we try to understand what caused the drawdown and whether there are research lessons that can be applied to limit the peak to trough drawdown or speed up the recovery from a drawdown without giving up too much of the long-term average information ratio.

We study the actual portfolios during the really good periods in the simulation to make sure we would have viewed these portfolios as properly diversified and not too risky at the time of the investment. All too often, the best simulated information ratio depends on one or two strings of truly exceptional performance. Was this due 100% to the investment process, or partly to some “luck” in having a few big positions that went the right way when some unexpected (by the model) events occurred and worked out well.

For example, your model puts you big-time long US Treasuries in the summer of 1998. Then LTCM happens, even though your model’s position was based completely on other factors, there is a market flight-to-quality that greatly benefits your bond position.

We do not want to pooh-pooh good luck, as being in the right place for good luck to strike is part of one’s expertise. But we do want to make sure that our portfolios are “investable” at all times during the simulation, in the sense that reasonable portfolio managers would be willing to implement such portfolios. Toward this end, we modify the portfolio construction objective function to first look for a high return to risk ratio, and then to explore some smaller trade-offs, preferring portfolios with more diversified positions, lower transaction costs, better liquidity, etc. Some of this work can be done quantitatively, and some is in the art of the research process. The result is a judgment as to which investment process to choose for implementation that is not based solely on the simulated information ratio, but is always a trade-down from the “best” simulation.

**Improving adaptability to changing markets**

We know that the structure of markets evolves over time and that in some cases the structural change can be quite abrupt. We prefer dynamic Bayesian modeling processes because these methods intrinsically manage the process of updating expectations as new information becomes available in a manner that respects the fundamental laws of probability.

Just using a Bayesian system is not enough, however, to ensure sufficient adaptability for real world investing. There are many parameters and factors to set and to choose in a Bayesian forecasting system, as in any dynamic forecasting system, and one needs
to pay special attention to the parameters, factors, and modeling structure that balances adaptability with good simulated performance.

One can think of this issue as a sub-set of the data-mining problem. We all data-mine in our research process, because essentially that is what research is all about. But we have to be very careful not to “over-fit” a particular historical period while limiting the flexibility to adapt to some new market forces and structures that were not present in the simulation period. When we were discussing the challenge of simulation results that were “too good”, we noted that one needed to study carefully the period in which these results occurred. Here we want to go beyond that caution flag and carefully introduce flexibility and dynamic adaptability into our models for certain specific reasons.

In our case, performing research on global financial markets, we feel we want to encourage dynamic adaptability in our models for the challenges created (a) when countries decide to go their own way in conducting and setting policies and (b) when countries coordinate policies. One may also worry about the challenges when economic conditions and market forces conspire to alter (even if temporarily) the trade-offs among different asset classes, such as currencies, government bonds, high yield bonds, equities, commodities, and real estate. Even if some of these asset classes are not contained as explicit investments in our models, changing asset allocation in dynamic markets can impact your asset class indirectly and in very important ways. We will tackle the challenge of country similarities and differences here, as well as how our approach to different styles of models and choice of factors in the fundamental model handles the latter issue.

As usual, our solution to the issue of coordination or non-coordination among country policies is complex and involves some art as well as some quantitative discipline. Here are a few things we do to improve model adaptability, while hopefully not giving up too much in terms of simulated information ratios.

We treat special periods with special care. For example, if our currency models made a lot of money in the 1996-1998 run-up to the introduction of the Euro, when the convergence theme was critical, we are careful not to extrapolate those results into the future. We are happy our models made money in that period, as this is an example of adaptability, but we are equally careful not to expect a repeat performance since the causal event is unlikely to be repeated. Other periods of which to be aware are (1) mortgage market profits in 1995-1997 after the big sell-off in the spring of 1994, (2) equity profits in the exuberant bull market of 1997-1999, (3) commodity market profits in the 2004-2005 bull market, etc.

By research and testing (some data-mining), we try to find the sweet spot in the information time decay parameter used in our dynamic Bayesian models. We view newer information as more valuable than past information, so we set our rate of learning (or our rate of forgetting) to discount older information. But the choice of the time decay parameter is critical. We use a faster time decay of the variance and correlation estimates than for the factor process. That is, we want our risk and
correlation structure to adapt very rapidly, while we tend to allow our models a slower adaptation process according to the way specific factors impact our security excess return forecasts.

**We also vary the time decay parameter for the factors, depending on the type of model we are building.** Models based mostly on fundamental factors sometimes require a longer time period for adaptation – or alternatively they may benefit from the stability of a slower forgetting rate. By contrast, models whose factors place them in the “technical” or “chartist” class of investing tend to benefit from much more rapid time decay parameters than in fundamental models. In fundamental models, factor selection is based in part on economic theory, in which only a very few factors are used to capture the major elements of the financial environment. In technical models, factor selection is designed to identify past market movements of significance (from noise). From our perspective, it makes good intuitive sense that fundamental models some times needs a longer information time decay process.

**We use shrinkage with great care.** Shrinkage is a Bayesian technique that is useful for extracting weak signals from noisy data when a particular theoretical idea is felt to be useful across an entire set of securities. For example, exchange rate movements are theoretically linked to monetary policy changes, which in turn are linked to the shape of the yield curve that the combination of monetary policy decisions and market environment produces. In the general version, the link from the shape of the yield curve to exchange rate returns is not expected to be different for different currencies.

Or take an example from the technical world. The ratio of a short-period moving average to a long-period moving average is considered a good buy-sell indicator. Ratios above one indicate a buy signal, and ratios below one indicate a sell signal. Technical analysts or chartists are proud to be able to apply their pattern recognition methods to any historical sequence of price data, regardless of the securities or asset class. So, in keeping with the technical theory that pattern recognition processes are independent of the securities chosen for analysis, we usually apply shrinkage to the technical factor estimation process.

As one can see, the shrinkage method allows one to use data from an entire set of securities to get an improved estimate of the relationship between the selected factor and the excess returns from the set of securities. This is a powerful concept and statistical method. In many, many models, the addition of the shrinkage method compared to using independent factor estimation works to raise simulated information ratios by a considerable amount. One must remember, however, that shrinkage is best applied only when one is confident that the factor relationship is robust across the set of securities.

**Typically, our models fall into the mixed shrinkage category.** That is, we use shrinkage for a specified set of factors and leave another specified set of factors to be estimated without shrinkage. This latter set without shrinkage usually includes the drift or constant term. The drift or constant term can be intuitively considered as an
estimated Bayesian bias term for each security’s excess returns, given the factor set chosen for the model. Since we are not usually comfortable (there are always exceptions) with the assumption that our models have the exact same biases for each security or asset class, we typically avoid using Bayesian shrinkage for the constant term. There are no provable answers as to when to apply shrinkage, whether across every factor and every security in one’s model, to a mixed version, to not using shrinkage at all.

In our research, we have tended to observe that choosing factors amenable to shrinkage and using a full shrinkage version can produce higher information ratios for many simulation periods. But there is a price. In global models, full shrinkage methods do not allow for countries to go down different cultural or regulatory paths. Thus, in periods dominated by similar policy objectives if not out-right policy coordination, full shrinkage may provide a much better factor estimation process. In periods, in which countries choose to go their own ways, full shrinkage may impede the model’s ability to learn quickly about the new environment and the new policy structure. Or worse, full shrinkage runs a risk in a global model that it may be difficult if not nearly impossible for the quantitative system to understand if countries have different policy-making dynamics or different regulatory structures that effect factors for their country differently than in other countries. This problem will be minimized when countries share common objectives and common problems, but it will be exposed as a serious risk when countries choose different economic objectives and/or face different economic challenges. It is this set of observations about the long-term need for model flexibility when working with global financial securities that has driven our preference for mixed shrinkage models over full shrinkage models, despite the observation that customized full shrinkage models can out-perform on a simulated basis over specific periods, some of which are quite long and impressive.

**Mixing types of factors in one model or building multiple models?**

Choosing factors for dynamic Bayesian models is one of the most important steps in the modeling process. Factor selection involves making key judgments about the relevance of factors across different market environments, about how factors relate to each other in theory and in practice, about the ease and reliability of observing factors values, etc.

Over time, our experience in building models and observing their performance under real investing situations has led us to a set of guidelines for factor selection as well as convinced us that a multiple-model research approach is better than a single-model research approach, even if we choose to implement only one model. To understand the theoretical and practical reasons for our conclusion that multiple models are the better research approach, one first has to examine our approach to factor selection.

Our conclusion that multiple models is the better way to go is new for us, in that we have only been working this way for the last four to five years. When we first started in the early 1990s, we were just trying to build one really good and practical model for global investing. As the time lengthens over which we have been both active Bayesian
researchers and active investors in our models, we have experienced many different types of financial environments and seen our share of market disruptions. We have come to value having a robust and diversified research program.

In addition, a number of years ago, our research team was asked by a client to build a set of stylized models, mostly for marketing and strategic purposes and not for investing. The client’s instructions were to only use economic factors in a fundamental model and only use technical factors in a technical model. The client was specifically interested in helping its different clients, which it grouped into “fundamental” and “technical” camps, based on how they thought about market developments. In addition, there was an “eclectic” camp that used the trendy factors of the current market environment. Prior to building these stylized models of global securities, we had focused our research on building the one best model, which in our case would have fallen mostly, though not completely, in the “fundamental” camp.

We relatively easily and quickly built the models that the specific client had requested, which were used quite successfully in gaining a better understanding of the key drivers of each stylized camp of investors. What then happened was that internally and apart from the work required by the client, in our own research process we became extremely interested in comparing and contrasting stylized models, and even building models of models. When we started this free-form research process, we were not quite sure where it might lead, but we felt we were learning a lot about the factor selection process and that the research was worth the effort. Here are some of the lessons we have learned and the factor selection guidelines we have developed.

Do not mix factor types in one model. We have learned that to achieve long-term robust performance it appears to work better to keep technical factors in technical models and fundamental factors in fundamental models rather than mixing the two in search of the “Holy Grail” of models. The reason in terms of economic theory appears to be in the way different factors contain information about markets.

Technical factors are those factors derived solely in some formulation, which may be very complex, based only on the price history of the security in question. While fundamental factors are generally market or economic data which can be formulated in any manner of ways and are suspected of having a key relationship to the security in question. By definition, then, the technical factors in some way contain the information of how the market reacted to the universe of fundamental factors. If one combines the factors reflecting the outcome of the fundamentals with the fundamental factors themselves into one model, then the system, even a dynamic Bayesian one, may have difficulty sorting out the long-term robust relationship between factors and security returns, because the information is mixed between more causal factors and more reflective factors. This could lead to, but does not necessarily lead to, a less stable correlation of the factors, and it may make it more likely that spurious correlations can drive model results for certain periods of time – to the short-term benefit of the model’s performance but to the detriment of the long-term robustness of the model. Our
research in this regard is by no means “final” or conclusive, or even all that quantitative. We have merely come to an intuitive understanding of how factors can work together or work against each other, and for now, we have felt it best to create a guideline for factor selection that focuses on separating types of factors into different types of models.

Let’s take another perspective on this issue. Suppose one set of factors is based on a particular economic or financial theory, and the other set of factors is based purely on received learning from the historical data. As such, there is really no gain in information from combining factors obtained from a fundamental theory with those derived from data patterns that reflect how markets actually behaved. Doing so will make the value of the theoretical construct less useful, or perhaps even useless. Put another way, we will not learn anything from evaluating our past prior expectations derived from our quantitative estimation process, if we cannot analyze why the estimates we get from our models yield forecasts that are either consistent or inconsistent with our theories regarding what is driving market prices. Combing factors from technical and fundamental approaches makes it nearly impossible to understand whether our fundamental theories and factor choices are appropriate because too much similar information is contained in both sets of factors and the models are unlikely to be able to separate it consistently over time.

Please note that it is not enough to show in a matrix of factor correlation pairs, that one’s technical factors are relatively uncorrelated with one’s more fundamental factors. One needs to consider the information content of the entire set of technical factors as compared to the information content of the entire set of more fundamental factors. Because one if mixing causality concepts with reflective concepts, there is the potential for unstable correlations of the information content between the set of technical and the set of fundamental factors, as well as unstable factor to factor correlations.

Technical factors need to be kept as simple as possible and limited to a very few, just one, two, or at most three. Technical analysts and chartists have some very complex ways of visually describing patterns, such as “head and shoulders”, etc. Our research into technical factors suggests that in a dynamic Bayesian framework, simple moving averages and ratios of moving averages provide better results than complex concoctions. Also, we have noted that as one adds new technical factors to the mix, there is virtually no new information being added, so fewer factors are better than many.

Technical factors often require rapid time decay parameters. Technical information is somewhat more fleeting than fundamental information, and so the rate of learning (rate of forgetting about the past) needs to be faster than with fundamental factors and fundamental models.

Fundamental factors should be linked, if possible, to the way market participants “talk” about the factor. There are always an infinite number of ways to manipulate a given piece of financial or economic data. Our approach is to use the method most generally utilized in the market by sophisticated players. If the best global market analysts are talking about the shape of the yield curve in terms of the simple spread
between a long-rate and a short-rate, then that is probably a good way to measure the factor for research purposes.

**Fundamental models can have one or two more factors than technical models**, but even so, models seem to do better over long time periods with fewer factors. We once used six to eight factors in our fundamental models and now we work with only two or three, and rarely four. The problem over a long time period is that factors contain overlapping information about markets, and that one is better off with fewer factors that are clearly different from each other, as opposed to gaining a marginally better description of the environment by adding overlapping factors. For example, in choosing economic factors, one would only want to include one measure of economic growth, rather than a potpourri of retail sales, industrial production, employment, etc. In a Bayesian model when two or more factors essentially contain similar and overlapping information, then the model starts to build complex (and not always stable) factor relationships that intuitively appear as if the model is using one factor to “drive” a return forecast and the related factors to “hedge” the forecast. But the stability of the “driving” versus “hedging” factors is often in doubt.

**Choosing factors to maximize model interpretability is a key objective.** Black-box models can produce some of the best simulations and some of the worst actual results. Bayesian factor models are a long way from a black box. It still pays good dividends in terms of long-term actual performance in real markets if the model can be interpreted and understood as easily as possible. The drive for an easily interpretable model is one of the key trade-offs with the higher simulated information ratios available in models with a few extra factors, or other twists that give them an edge (some times a big edge) over particular periods of time, some of which are quite long.

One of the key advantages of a more interpretable and better understood model is that one can more easily figure out why it is not working in a given market environment. Our implementation approach is to choose a preferred model, while always tracking the performance of the alternative models. Since the alternative models offer reasonable long-term performance, we have fall-back portfolios with different characteristics if the current financial environment does not appear suited to our preferred model. Since short-term, quick-fix solutions are not usually good for long-term investment results, just knowing when to back-off (reduce risk) can be a very good thing, and the confidence with which the portfolio manager can make these decisions is increased when the model is more interpretable and better understood.

We cannot emphasize this point about interpretability enough. The better we understand the how and why of our research models, the better decisions we will make in actual investing about when to run our models at full risk or when to dampen the risk taking or even switch (partially or fully) to a more appropriate model.

**Multiple research models may prove better than using a single model research approach.** When we put all of these ideas and concepts about factor selection together, we have come to the conclusion (for now, and always subject to change
depending on future research) that we are better off with several research models, all of which perform reasonably well over long time periods in simulations, but none of which has as high an information ratio as could be obtained from a single, mixed-style, optimized model. Furthermore, the correlations between any two models are, hopefully, less than 0.7 and sometimes less than 0.5, meaning that we are getting some model diversification for our research efforts.

Moreover, it is only a short step from building multiple models to building a Bayesian model of models. It turns out this approach can add some types of information not easily included in the single model approach. For example, we have developed a proprietary measure of how strong the tension is between technical models and fundamental models, which serves as a factor in the model of models, and helps determine the allocation to a given model.

As it has developed, for now, we have settled on three models for each set of securities in the portfolio. That is, we build “fundamental”, “technical”, and “sentiment” models.

The “sentiment” model is a model designed to answer the question “what are the discounted expectations of typical market participants in terms of excess returns, risks, and correlations?” Sentiment models serve as a base line for our risk analysis work, but they also turn out to be useful in comparing patterns of excess returns and risks to our stylized fundamental and technical models.

Moreover, sentiment models tends to adapt faster to new market structures, so even though their simulated information ratios are a little lower than either the fundamental or technical models, there are certain market conditions in which they can out-perform. These market conditions are not easily quantifiable, but they are recognizable by experienced practitioners, so long as the styled models are relatively interpretable. That is, when market structure is changing for known reasons, and these reasons are likely to cause issues for either the technical model or the fundamental model (or both), then the portfolio manager can allocate more heavily to the faster-adapting sentiment model, if only for a short period of time.

III. A Selection of illustrative simulated experiments with Bayesian models

For this informal report, we have decided to present simulated experiments based on our Fundamental and our Technical Model, so as to focus attention on two specific styles of investing and to provide a nice contrast in the model simulations.

What is presented are data from our simulations, making them as realistic as possible in terms of the actual conditions in the investing world. Transaction costs are estimated by
a team of traders and monitored constantly. These investment programs use currency forwards and exchange-traded futures contracts to execute positions, so only margin is required to create exposures, and margin and uninvested cash earn interest at a 0.5% haircut to prevailing money market rates. All trades are assumed to be conducted at the close of business in each major regional time zone. The experiments shown here are from weekly models for the week ending on Monday’s close. Based on the pre-simulation period, we have calibrated the parameters of the objective function to attempt to produce portfolios in the 12% to 14% volatility range, on average and over time, where volatility is measured as the annualized weekly standard deviation of excess returns. During the simulation period, the actual volatility of each investment programs differs from each other, on average and over time. The simulation period is from January 2000 through March 2007.

The first two tables present comparisons by “Information Ratio” and by “Sharpe Ratio”.

There are four models being compared:

(1) Fundamental Currency  
(2) Fundamental Global Macro  
(3) Technical Currency  
(4) Technical Global Macro

The Fundamental forecasting model uses three factors observable in the market and related to the current policy actions of the central bank, the shape of the yield curve, and the relative performance of equities versus bonds. The Fundamental forecasting model produces estimates of excess returns, volatility of the excess return forecasting errors, and the correlation structure of the forecasting errors, which are used as inputs into the modified mean-variance optimization system to produce portfolios for investing for the Fundamental Currency and Fundamental Global Macro portfolios.

The Technical forecasting model uses three factors observable in the market and related to the ratio of two daily moving averages of different lengths for the price of the securities, and two additional technical measures to capture trading signals from historical price data. The Technical forecasting model produces estimates of excess returns, volatility of the excess return forecasting errors, and the correlation structure of the forecasting errors, which are used as inputs into the modified mean-variance optimization system to produce portfolios for investing for the Technical Currency and Technical Global Macro portfolios.

The only difference in the Currency and Global Macro portfolios are the allowable securities. The Currency portfolio uses a wider range of minor currencies than the currency section of the Global Macro Portfolio. The Global Macro Portfolio invests in a selection of equity indices, government bonds, and commodities, in addition to currencies.
The first row of each table provides the Information Ratio (Annualized Excess Returns divided by Annualized Standard Deviation of Excess Returns) for our current base-case models, or the Sharpe Ratio (Annualized total returns after fees divided by annualized standard deviation of total returns). The Sharpe Ratio data includes fees and is based on total returns, which includes the return on cash held as margin or to support credit lines. The Information Ratio data is based on excess returns before fees and not including any cash returns.

The second row of each table show the results of an experiment relative to the base case where the beta coefficients on each factor are estimated using a recursive regression approach rather than a Bayesian inference approach with a time-decay for learning. The covariance estimates continue to use a Bayesian inference system, as in the base case models. The Bayesian inference models are uniformly superior. The benefits of the Bayesian learning for factor beta estimation are more pronounced for the currency portfolios than the Global Macro portfolios.

The third row of each table show the results of an experiment relative to the base case where the covariance matrix is estimated using a recursive approach rather than a Bayesian inference approach with rapid time-decay for learning. The beta coefficient estimates for the factors continue to use a Bayesian inference system, as in the base case models. The Bayesian inference models are uniformly superior with no major biases related to the particular model being studied.

The fourth row of each table show the results of an experiment relative to the base case where both the beta coefficients for the factors and the covariance matrix are estimated using a recursive approach rather than a Bayesian inference approach with time-decay for learning. This is a combination of the first two experiments. The Bayesian inference models are uniformly superior with no major biases related to the particular model being studied. The currency models do much better in the full Bayesian mode, while the Global Macro models are negatively effected by a lack of Bayesian learning, but not by as much as in currencies alone.

The fifth row is a different kind of experiment. In this case, we are looking at portfolios in which the investment restriction of no US dollar net directional exposures has been applied. That is, the currency section of the portfolios is always US dollar neutral, with all the exposures in terms of non-US dollar cross exchange rates. These simulations were done at the request of a client, and they are present here mainly to show the type of research customization that is possible. The results indicate that moving to a US dollar neutral stance over the entire simulation period can cost from 30% to 40% of the Information Ratio. Put another way, the models do a pretty good job making profits from US dollar directional exposures on average and over time.
<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Current Models</td>
<td>1.07</td>
<td>0.78</td>
<td>1.23</td>
<td>1.22</td>
</tr>
<tr>
<td>Without Bayesian Beta Coefficient Learning</td>
<td>0.64</td>
<td>0.70</td>
<td>0.52</td>
<td>1.05</td>
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<tr>
<td>Without Bayesian Covariance Learning</td>
<td>0.84</td>
<td>0.63</td>
<td>1.14</td>
<td>1.09</td>
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<tr>
<td>Without Bayesian Beta Coefficient or Covariance Learning</td>
<td>0.40</td>
<td>0.56</td>
<td>0.34</td>
<td>0.83</td>
</tr>
<tr>
<td>USD Neutral in FX Sector</td>
<td>0.58</td>
<td>0.52</td>
<td>0.86</td>
<td>1.13</td>
</tr>
</tbody>
</table>
## Simulated Sharpe Ratios (12%-14% risk target range)

<table>
<thead>
<tr>
<th></th>
<th>Fundamental Currency</th>
<th>Fundamental Global Macro</th>
<th>Technical Currency</th>
<th>Technical Global Macro</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current Models</td>
<td>1.48</td>
<td>0.95</td>
<td>1.86</td>
<td>1.76</td>
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<tr>
<td>Without Bayesian Beta Coefficient Learning</td>
<td>0.73</td>
<td>0.83</td>
<td>0.59</td>
<td>1.57</td>
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<tr>
<td>Without Bayesian Covariance Learning</td>
<td>1.08</td>
<td>0.74</td>
<td>1.70</td>
<td>1.55</td>
</tr>
<tr>
<td>Without Bayesian Beta Coefficient or Covariance Learning</td>
<td>0.46</td>
<td>0.63</td>
<td>0.42</td>
<td>1.10</td>
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<tr>
<td>USD Neutral in FX Sector</td>
<td>0.71</td>
<td>0.59</td>
<td>1.12</td>
<td>1.53</td>
</tr>
</tbody>
</table>

The following four sets of tables are based on total return simulated data, after all fees, and including a return on cash holdings.

These tables are presented to provide some additional detail on how the simulated investment program performed through the years.

| Project Name                  | Start Date   | Total Return Since Inception | Total Return for Y2000 | Total Return for Y2001 | Total Return for Y2002 | Total Return for Y2003 | Total Return for Y2004 | Total Return for Y2005 | Total Return for Y2006 | Total Return for Y2007 | Largest Peak to Trough DrawDown Since Inception | Date of Starting High Water Mark for this episode | Date of Trough after Peak for this episode | High Water Longest number of periods between two High Water Marks | Date of Starting High Water Mark for this episode | Date of Ending High Water Mark for this episode | Number of new High Water Marks After the initial Value | Sum of number of periods between High Water Marks | Average number of periods between High Water Marks | Volatility | Daily Standard Deviation Last 100 Days | Daily Standard Deviation Since Inception | Annualized Standard Deviation Last 100 Days | Annualized Standard Deviation Since Inception | Value at Risk (99%) Last 100 Days | Value at Risk (99%) Since Inception | Risk-Return Ratio | Sharpe Ratio |
|------------------------------|--------------|-------------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|-----------------------------------------------|-----------------------------------------------|-----------------------------------------------|-----------------------------------------------|-----------------------------------------------|-----------------------------------------------|-----------------------------------------------|-----------------------------------------------|-----------------------------------------------|-----------------------------------------------|
| Start Date                   | 04 Jan 2000  | 04 Jan 2000                   | 04 Jan 2000            | 04 Jan 2000            |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Returns                      |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Total Return Since Inception |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Total Return for Y2000       |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Total Return for Y2001       |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Total Return for Y2002       |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Total Return for Y2003       |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Total Return for Y2004       |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Total Return for Y2005       |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Total Return for Y2006       |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Total Return for Y2007       |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Largest Peak to Trough DrawDown Since Inception |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Date of Starting High Water Mark for this episode |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Date of Trough after Peak for this episode |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| High Water Longest number of periods between two High Water Marks |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Date of Starting High Water Mark for this episode |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Date of Ending High Water Mark for this episode |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Number of new High Water Marks After the initial Value |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Sum of number of periods between High Water Marks |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Average number of periods between High Water Marks |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Volatility                   |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Daily Standard Deviation     |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Last 100 Days                |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Daily Standard Deviation     |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Since Inception              |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Annualized Standard Deviation Last 100 Days |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Annualized Standard Deviation Since Inception |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Value at Risk (99%) Last 100 Days | $1,865,449  | $1,460,035                    | $2,196,450             | $1,704,809             | $1,559,432             | $1,687,035             | $1,601,219             | $1,669,077             | $1,559,432             | $1,687,035             | $1,601,219                    | $1,669,077                    | $1,559,432                    | $1,687,035                    | $1,601,219                    | $1,669,077                    | $1,559,432                    | $1,687,035                    | $1,601,219                    | $1,669,077                    |
| Risk-Return Ratio            |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
| Sharpe Ratio                 |              |                               |                        |                        |                       |                       |                       |                       |                       |                       |                               |                               |                               |                               |                               |                               |                               |                               |                               |                               |
Our research program is focused in several different directions.

Our first research objective is to provide realistic models for two styles of investing (i.e., Fundamental, Technical) that will be well-performing out of sample and going forward. We use a Sentiment Model to provide volatility and correlation information and to serve as a base-line case of evaluating our Fundamental and Technical models. Toward this end, we have a program to examine different factors and different factor transformations. We are also looking at adding new securities, where we think they fit the required assumptions. Finally, in this part of our research program, we are testing various systems to allocate within a Fund of Models, among our stylized models. Toward this end, we have been developing some new factors that measure the tension between fundamental and technical forecasts and observing how different styles of investing perform when the tension between fundamental and technical forecasts are at high levels or at low levels.

Our second research objective is to use our systems to answer market questions. We can drill-down quite deeply into our systems, to try to answer questions, such as is the US dollar weak (strong) or the Euro strong (weak), since we have broken out the relative factor contributions in such a way as to shed light on this question. We can also explore the implied utility function of difference central banks and try to asses whether they are changing their policy tools or policy objectives, as can be the case when leadership at a central bank changes.

Our third research objective is to apply our Bayesian systems to financial estimation challenges not directly related to portfolio construction, yet to serve as informative research for portfolio managers and traders. For example, currently, we are building political forecasting models, with some hints of early success.

We hope this informal report on our research methods, our progress, and the lessons we have learned over the years has provided some insights into the practical application of Bayesian-based forecasting systems in the world of asset management.

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References – currently being prepared. If you would like a copy of the next draft of this informal research report, including references, please let me know at blu.putnam@eqapartners.com.