

## Macroeconomic Simulation Analysis for Multi-asset Class Portfolio Returns

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### ABSTRACT

Macroeconomic Simulation Analysis provides an in-depth insight to a portfolio's performance spectrum. Conventionally, portfolio and risk managers obtain macroeconomic scenarios from third parties such as the Federal Reserve and determine portfolio performance under the provided scenarios. In this paper, we propose a technique to extend scenario analysis to an unconditional simulation capturing the distribution of possible macroeconomic climates and hence, the true multivariate distribution of returns. In general, this is referred to as a top-down approach. We start with forecasting nearly 30 macroeconomic variables using Bayesian Vector Autoregression (BVAR). BVAR is used to avoid overfitting of the forecasting model. Using the model residuals, we fit copula over the marginal error distributions of each of the factors, thus taking into account the uncertainty and tail risk. After fitting the BVAR, marginal error distributions, and copula, we simulate the distribution of macroeconomic scenario paths. By using Monte Carlo simulation, coupled with asset class return regression models, we approximate the full unconditional multivariate return distribution for the asset classes. In this case, the variance and correlation in returns comes from two sources—the macroeconomic path simulation and the uncertainty in asset class returns under said macroeconomic path. This technique gives a portfolio manager the understanding of the extreme tail risk and asset class relationships, the macroeconomic variables uncertainties and correlations. The proposed methodology adds value to the existing scenario analysis tools and can be used to determine which types of macroeconomic climates have the most adverse outcomes for the portfolio. This provides a broader perspective on value at risk measures, thereby allowing more robust investment decisions to be taken.

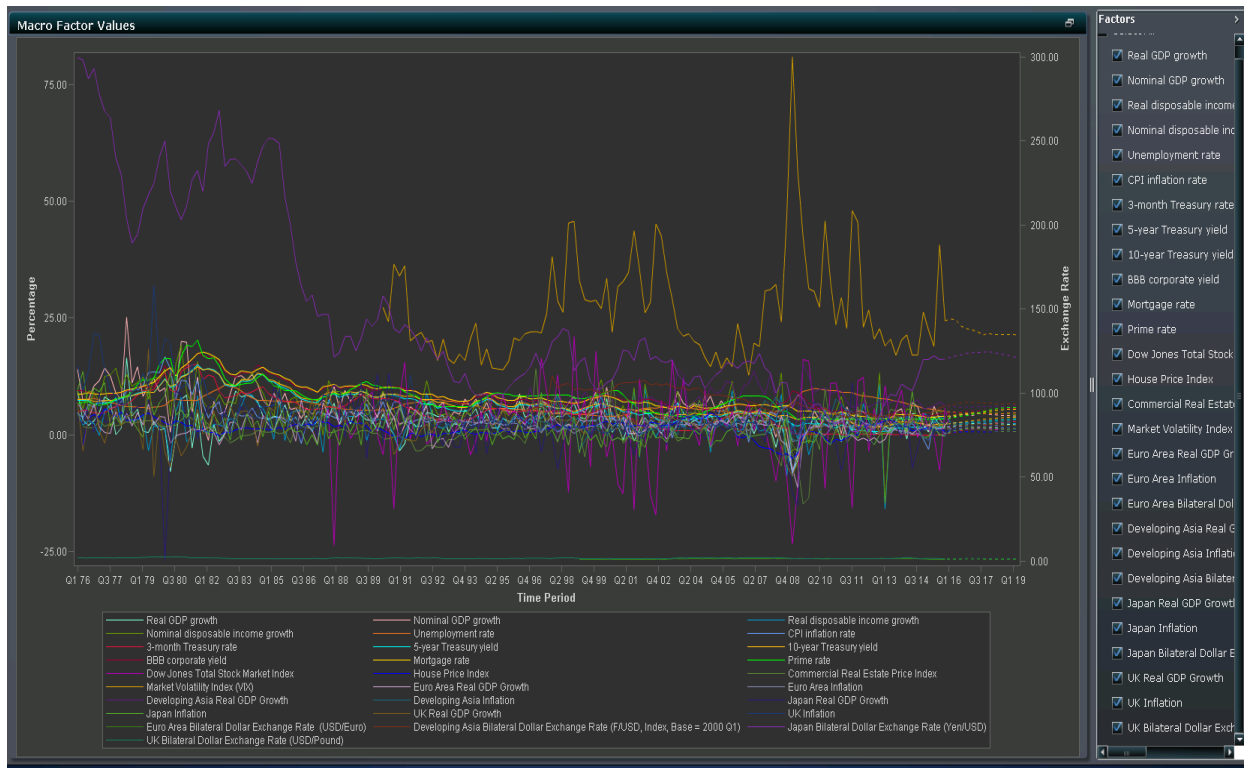
We explain the use of SAS procedures like VARMAX, COPULA (in SAS/IML<sup>®</sup> software), and OPTMODEL to perform the entire analysis in a few steps.

### INTRODUCTION

Any diversified portfolio consists of investment in different asset classes. Typically, these include equity, fixed income, real estate, and so on. Each asset class has its own significance that is defined by its risk and return characteristics. Returns of these asset classes fluctuate due to a variety of factors. An interesting area of research is to study the movements of these asset classes due to the movement in macroeconomic variables. Portfolio managers like to model the state of a portfolio at any future period of time under different economic scenarios. A lot of research has been done around scenario analysis. Typically, this includes regression models where a functional form is assumed between the macro economy and the economic variables. Scenario analysis includes testing portfolio performance by disturbing the macro factors under scenarios like Base, Adverse, and Severe. In this paper, we try to modify the traditional scenario analysis technique by taking a step forward and capturing the unconditional behavior between the macro economy and portfolio returns, rather than restricting it to a set of few scenarios. A top-down approach is adopted where the macro economy is forecasted and then portfolio returns are forecasted using regression models. The steps followed by us are explained in the following sections.

### MACROECONOMY AND HISTORICAL DATA

For this study, we use a total of 28 macroeconomic factors and we try to use as many data points as possible. Figure 1 shows a plot of different macroeconomic factors plotted against time. We use the data published by the Federal Reserve for these macro variables.



**Display 1. Time Series of 28 Macroeconomic Variables Used for Study**

## FORECASTING MACRO ECONOMY

Forecasts of macroeconomic variables are traditionally obtained using autoregressive models. However, our study implies that these macroeconomic variables are themselves highly correlated and modeling them independently is not the best idea. To solve the problem, vector autoregressive models are used where forecast of a variable depends not only on the previous lagged values of the variable itself but also on the lagged values of other variables. However, this leads to over parameterization of the model with too many parameters to be estimated. This might result in misleading relationships and results. One way of overcoming the problem of over parameterization is to assume only a few lags and exclude all other previous lags in the model. This can be thought of as assigning 0 to the parameters, defining gravity of these lags without any evidence from data. These assumptions have been found to be too extreme to modelers and hence Bayesian VAR have become popular.

### BAYESIAN VECTOR AUTOREGRESSION (BVAR)

Like any Bayesian technique, BVAR combines the prior beliefs of the modeler along with the evidence from data collected to make a more accurate conclusion of the relationship between variables. The modeler's prior beliefs help to avoid the problem of over parameterization. The user has a say about his or her beliefs regarding the coefficients and then a statistical procedure will revise them based on the data points collected. Hence, BVAR does not make sharp distinctions. The rest of the setup mimics the process.

There are multiple techniques available in literature to specify the prior beliefs about the coefficients. In this paper, we concentrate on a recently popular prior called the Minnesota prior. In this, once a set of variables to be used are finalized, prior probabilities about the coefficients are stated in the form of assigning a best guess and a measure of confidence around the guess. The best guess is based on a random walk hypothesis, where all coefficients, except the most recent value of the variable are set to 0 and the most recent one is set to 1. The BVAR has two hyperparameters to be estimated—the confidence ( $\lambda$ ) around each prior and a scale factor ( $\theta$ ). Once these hyperparameters are set and all coefficients are estimated, we can produce the forecasts for the next few time periods. A detailed

discussion of the BVAR can be found in the article, “Improving Economic Forecasting with Bayesian Vector Autoregression” (Todd 1984).

## PROC VARMAX FOR IMPLEMENTING BVAR

PROC VARMAX in SAS/ETS® software provides the functionality to perform Bayesian Vector Autoregression. To do so, we use the PRIOR= option to specify the hyperparameters lambda and theta discussed above.

Here is the syntax for using PROC VARMAX to perform BVAR:

```
PROC VARMAX DATA = MACROECONOMY OUTEST = estimates;
  MODEL Real_GDP Unemployment_Rate CPI_Inflation_Rate /
    P = 1
    PRIOR = (LAMBDA = 0.9, THETA = 0.1)
  ;
  OUTPUT OUT = FORECASTS
    LEAD = 12
  ;
RUN;
```

In the above statement, we have assumed the three macroeconomic variables—Real\_GDP, CPI\_Inflation\_Rate, and Unemployment\_Rate to be modeled. In the prior statement, we specify the two hyperparameters of the BVAR model. Running this code produces an estimate of all coefficients in the model in the Estimates data set along with their forecasts in the Forecasts data set. The value of 12 for the LEAD= option specifies that PROC VARMAX is to submit to output the forecasts for the next 12 quarters.

## MONTE CARO SIMULATION FOR SIMULATING UNCONDITIONAL MACROECONOMIC SCENARIOS

PROC VARMAX gives us a forecast for the next 12 quarters. In the next step, our proposed methodology is to generate macroeconomic scenarios that we assume will cover all possible macroeconomic scenarios. To do so, we model the residual or error, which plays an important part in our modeling. The residual or error distribution gives us an idea of the part of the original distribution that our model could not explain. This in turn will be used for the simulation of macroeconomic scenarios. To model the error distribution, we assume that errors follow a Student’s t distribution. To estimate the parameters of the distribution, we use the maximum likelihood estimation technique on the out-sample error data. In our study, we build the BVAR model on data from 1990 to 2007 and test our model on 2007 to 2015, which we call the out-sample data. Since we have 28 macroeconomic variables, we fit 28 Student’s t distributions corresponding to each of these variables.

## COPULA FOR SIMULATION FROM ERROR DISTRIBUTION

In the previous section, we have fitted marginal error distributions on each of the macro variables. We then use copula to find the joint distribution from the marginal distribution and correlation between these variables. We find out the ranks of error of variables and Fit a t copula assuming uniform marginal.

PROC COPULA in SAS/STAT® software allows us to generate copula from marginal distributions as follows:

```
PROC COPULA DATA = res_ranks ;
  VAR Real_GDP_residual Unemployment_Rate_residual
  CPI_Inflation_Rate_residual
  ;
  FIT T / MARGINALS = UNIFORM METHOD = MLE
  ;
  SIMULATE / NDRAWS = 1000
    SEED = 0
```

```

MARGINALS = UNIFORM
OUTUNIFORM = simulated_errors
; RUN;

```

Once we specify the type of copula and marginal distributions, we simulate errors/residuals from the built copula in the same step. Thus, at the end of this step, we get simulated values from the copula in the Simulated\_errors data set. We simulate 1000 errors for each macro variable. It is to be noted that the simulated values need to be retransformed using the inverse cumulative distribution function (CDF) since we have simulated ranks and not the actual errors.

Once we get the simulated errors, we now generate the macroeconomic scenarios using the forecast we get from BVAR and the simulated errors. Adding error to the mean forecast of the BVAR model gives us the different simulated forecasts.

## EVALUATING PORTFOLIO PERFORMANCE UNDER UNCONDITIONAL MACRO ECONOMY

Having generated the different macroeconomic projections for the next 12 quarters that capture all possible conditions of macro economy, our task now remains to find how a given portfolio will perform under these macroeconomic conditions. To do so, we build regression models for each asset class that define the relationship between the macro economy and portfolio returns.

### ASSET CLASS RETURN MODELS AND VALUE AT RISK MEASURES

We used the REG and AUTOREG procedures in SAS/STAT to model the asset class returns as a function of the macro economy. We identified significant macroeconomic variables for each asset class using the variable selection option in PROC REG. Various transformations on them are used before the final model is implemented. These include log transformation, differencing, and so on.

PROC REG models one of the fixed income returns as a function of mortgage spread and BBB spread:

```

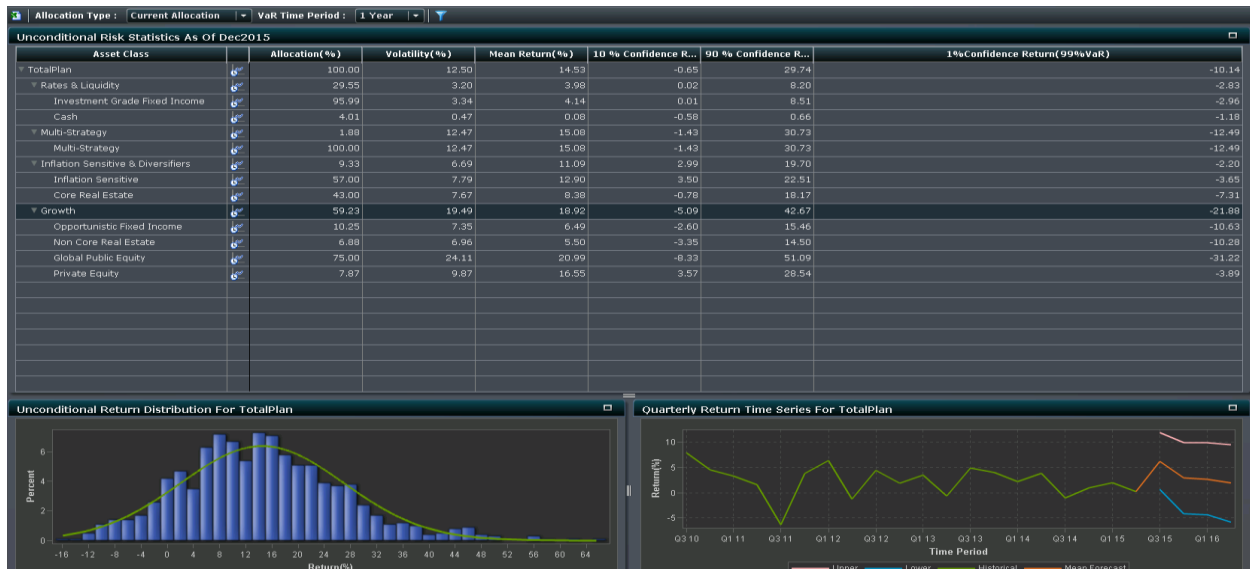
PROC REG DATA = return_data ;
    MODEL FI = Us_mort_spread US_bbb_spread
    OUTPUT OUT = predictions
RUN ;

```

Using these parameter estimates, we find out the performance of these asset classes under the 1000 macroeconomic climates. We report various value at risk (VaR) measures to find out the worst that could happen to the investment in the future period. These measures include mean return, volatility, 10% confidence return, 90% confidence return, and 1% confidence (99% VaR) return. The mean return gives an idea about the direction the portfolio is moving and the VaR measures will help the investor in deciding how much capital would be required to handle the portfolio losses in case of bad economic conditions.

## RESULTS

This paper discusses our method for assessing portfolio performance under different economic conditions. This gives us an edge over the traditional technique where only a few macroeconomic conditions are considered. Our simulation-based technique will try to cover the entire horizon of the macro economy. We have implemented the proposed methodology for a portfolio worth USD 1 billion. We have assumed a hierarchy for the portfolio where the proposed methodology is implemented at the lowest level. We then aggregate the forecasted returns based on the allocation strategy to find the returns at upper levels. The following figure shows the forecast for a period of one year for all asset classes and their hierarchies. A visual interpretation of the return distribution and forecasted series with confidence limits are shown below.



**Display 2. Simulated Forecast Returns of the Portfolio Using Proposed Methodology**

## CONCLUSION

The macro economy impacts the portfolio returns and hence, it is useful to understand the impact. The top-down approach allows us to model the macro economy first, forecast them, and then use the relationship to forecast the portfolio. Modern techniques like BVAR and PROC COPULA help in capturing minute details, and their sophisticated algorithms have an edge over the traditional algorithms.

## REFERENCES

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