***Risk Management***
April 2020

Published by Canadian Institute of Actuaries / Institut canadien des actuaires, SOCIETY OF ACTUARIES

RISK MANAGEMENT
APRIL 2020

# Macroeconomics Based Economic Scenario Generation

By Kailan Shang

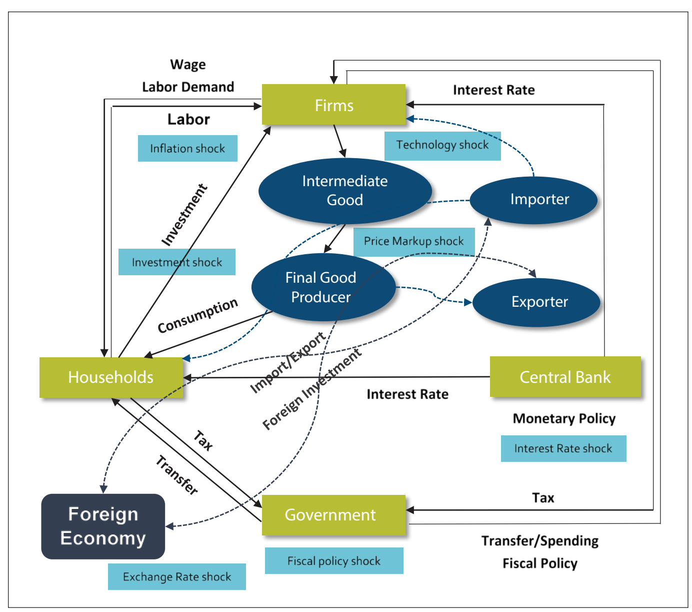
*Editor's note: The following article is the second in our April issue that focuses on economic scenario generators (ESGs). The article summarizes key points from the recently published research paper* Macroeconomics Based Economic Scenario Generation, *which was sponsored by the Joint Risk Management Research Committee and the Financial Reporting Section of the Society of Actuaries (SOA).*

*The paper looks at how dynamic stochastic general equilibrium and multifactor regression models can be combined to create an ESG. The full paper will be available in mid-April 2020.*

Economic scenario generators (ESGs) are used in the insurance industry to assess the uncertainty of economic conditions. Many real-world ESGs model asset returns and yield curves directly based on historical data. Others may model systemic risk separately using a macroeconomics model. However, some macroeconomics models can be data-driven as well. They may reflect the historical realization of an economic system but not necessarily how the economic system really works and other possible outcomes.

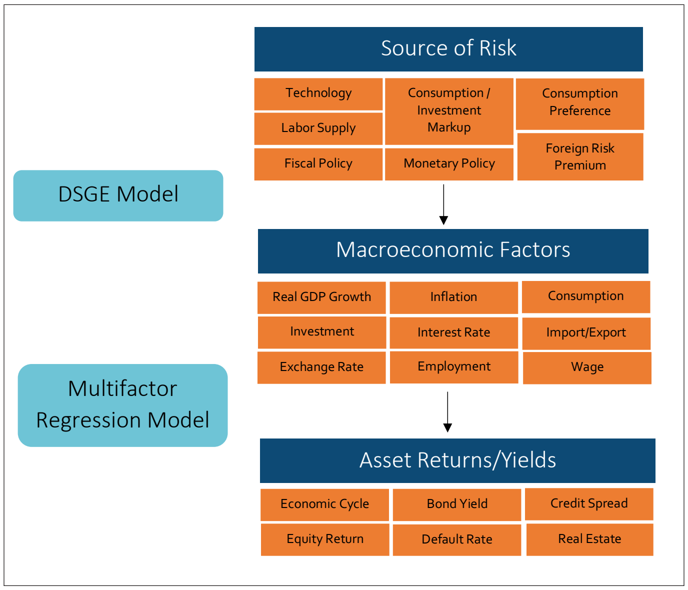
As a unique part of this new type of ESG, dynamic stochastic general equilibrium (DSGE) models are complex macroeconomics models and have been increasingly popular in central banks for analyzing monetary policies. Behaviors of economic agents such as households, firms, central banks and governments are usually defined explicitly, as shown in Figure 1. Based on that, observable economic variables such as real gross domestic product (GDP) growth rate, inflation, imports/exports and employment are estimated, while acknowledging economic shocks to the causes, such as labor supply and technology development, but not to the results, such as unemployment rate and GDP growth rate. With the given nonlinear cause-and-effect relationships defined, historical data is used to calibrate the models. As a potential candidate for modeling macroeconomic factors in an ESG, DSGE models are well equipped for maintaining economic patterns in individual scenarios and explaining the causes behind individual scenarios.

Figure 1
Sample DSGE Model Structure



This report builds an ESG that uses a complex macroeconomics model type to generate macroeconomic factors. The ESG consists of two parts: a DSGE model that generates macroeconomic factors and multifactor regression models that generate asset returns and bond yields (Figure 2).

Figure 2
Sample Structure of DSGE Model-Based ESG




With this structure, sources of risk are used to generate scenarios for modeled variables, instead of using the features of the modeled variables directly. The ESG is a real-world scenario generator that tries to model systemic risk based on macroeconomic models. Therefore, it is not mark to daily market conditions but reflecting economic patterns that persist in a longer time horizon. That means it is not suitable for hedging, financial option pricing, market consistent valuation and tactic asset allocation. It is more suitable for real-world strategy analysis such as strategic asset allocation, business planning, economic forecasting and long-term capital management. It may be used for reserving and capital management with an ongoing view of the business. As a rule of thumb, the ESG is not preferred for any decision making that considers important those patterns that persist less than a quarter. Although this may seem to be a disadvantage of this ESG, it allows users to incorporate their own forward-looking views by adjusting the input data, the models or the scenarios.

The U.S. economy is used as an example to demonstrate the DSGE model. Bayesian Monte Carlo Markov Chain (MCMC) method is used to calibrate the model based on historical macroeconomic data, while some model parameters are determined based on additional economic analysis to overcome the difficulties in model calibration. Economic factors generated by the DSGE model govern the systemic risk in the remaining process of the ESG. Asset returns and bond yields are simulated using multifactor regression models, reflecting both systemic risk and idiosyncratic risk.

Several regression models are tested, including linear regression, Lasso, ridge regression, elastic net, K-nearest neighbors (KNNs), classification and regression trees (CARTs), artificial neural networks (ANNs) and gradient boosting machines (GBMs). Given the data volume, overfitting is a critical issue in the example. ANN models showed very good estimation on the training data but the worst estimation on the validation data. With only 103 data records and many more model parameters, the superficial performance of ANN models is caused by overfitting with a lot more parameters than other models. CART models face the issue of overfitting as well, but less severely. In addition, the possible values predicted by CART models are limited given that the estimation is based on the average of a subset of historical data. KNN models had similar issues as CART models, with limited possible values and unsatisfactory prediction accuracy based on validation data. Linear regression models, especially elastic net models, did a good job predicting government bond yields, credit spreads and dividend yields. For public equity, real estate investment trusts (REITs), and commodities, idiosyncratic factors contribute much to the volatility. GBM models have better prediction accuracy than linear regression models for REIT equity returns. However, the improvement of accuracy may not justify a much more complicated model type. For succinctness, elastic net models are used for multifactor regression in this example. Elastic net models show relatively high prediction accuracy in most cases. Therefore, they are chosen to describe the relationships between asset returns and economic factors. Additional adjustments to the correlation among idiosyncratic risks are made to incorporate nonlinearity in the capital market during economic recessions.

Generated sample real-world economic scenarios can be compared to historical data (Table 1) or to market predictions to assess their reasonableness and identify areas of further improvement.

Because of the complexity of the DSGE model, efforts need to be made to mitigate model risk. Although we can rely on traditional measures such as log-likelihood and Akaike information criteria to compare the model against others,

Table 1
Moments of Asset Returns and Bond Yields

| Asset Class | | Mean (%) | | Standard Deviation (%) | |
|---|---|---|---|---|---|
| | | Historical | Simulated | Historical | Simulated |
| Treasury bond, 0 rate (for given term) | 1 year | 2.62 | 2.12 | 2.18 | 1.21 |
| | 2 years | 2.93 | 2.39 | 2.24 | 1.27 |
| | 3 years | 3.25 | 2.52 | 2.25 | 1.28 |
| | 5 years | 3.49 | 2.98 | 2.18 | 1.20 |
| | 7 years | 3.93 | 3.34 | 2.02 | 1.16 |
| | 10 years | 4.26 | 3.60 | 1.90 | 1.15 |
| | 20 years | 4.51 | 3.92 | 1.75 | 1.18 |
| | 30 years | 4.82 | 4.11 | 1.56 | 1.12 |
| AAA-rated corporate bonds | Credit spread | 0.47 | 0.60 | 0.58 | 0.64 |
| | Default rate | 0.00 | 0.00 | 0.00 | 0.00 |
| AA-rated corporate bonds | Credit spread | 0.58 | 0.71 | 0.78 | 0.68 |
| | Default rate | 0.02 | 0.03 | 0.08 | 0.34 |
| A-rated corporate bonds | Credit spread | 1.04 | 1.08 | 0.93 | 0.65 |
| | Default rate | 0.06 | 0.05 | 0.11 | 0.35 |
| BBB-rated corporate bonds | Credit spread | 1.83 | 1.80 | 1.08 | 0.67 |
| | Default rate | 0.18 | 0.15 | 0.25 | 0.30 |
| Public equity | Dividend yield | 2.00 | 1.93 | 0.54 | 0.60 |
| | Capital return | 2.04 | 2.28 | 9.33 | 5.49 |
| Real estate investment trusts | Cap rate | 1.56 | 1.21 | 0.44 | 1.51 |
| | Capital return | 1.43 | 1.49 | 9.09 | 5.58 |
| Crude oil | Total return | 2.37 | 2.48 | 16.18 | 11.99 |
| Gold | Total return | 1.37 | 1.45 | 6.75 | 5.92 |

it only assesses the goodness of fit to data inputs. It does not guarantee that generated models are reasonable. Sensitivities to the sources of risk can be examined to make sure that expected economic patterns are reflected in simulated scenarios. Range of forecasts can be compared with those provided by the Fed and professional forecasters. Individual scenarios can be checked to see if they preserve economic cycles and the coexistence of a low GDP growth rate, low interest rates, higher credit spreads and a bear equity market during economic recessions.

If the ESG is used as a tool for some regular tasks such as reserving and asset allocation, the calibrated model can be updated with new data or recalibration if deemed necessary. As the existing calibration may have already covered a long history, an additional quarter's data may not have material impact on the calibration, and therefore, recalibration frequency does not need to be quarterly but could be semiannual or yearly. However, with new data coming in each quarter, the starting point of the projection will be changed. The data input for the simulation part includes the latest two quarters' economic data and capital market data. They need to be updated before the scenario generation.

Overall, this research contributes to existing literature in three ways. First, it contains a step-by-step derivation of the DSGE model and details on model calibration. The purpose is to provide enough information for people to understand and be able to customize the DSGE model to reflect their own economic views. Second, it embeds DSGE models into economic scenario generation. DSGE models have been used for analyzing monetary policies but are seldom used in other areas. With a DSGE model-based ESG, users have the flexibility to incorporate prior knowledge of the economic system and the potential to analyze the causes of individual scenarios. It may be attractive for users who need to make decisions based on individual scenarios. The author is not aware of any previous efforts made in this area. Third, sample codes are made available for educational purposes.

The ESG presented in the report serves as an example of a DSGE-based scenario generator. By no means is it perfect, nor can it be used directly without adjustment. More efforts are needed to improve the ESG and make it attractive for practical applications. ■

Kailan Shang, FSA, ACIA, CFA, PRM, SCJP, is an associate director at Aon PathWise Solutions Group, Canada. He can be reached at *kevin.shang@aon.com*.