U.S. Macroeconomic Alternative Scenarios
The depth of the Great Recession and the slow pace of the recovery since mid-2009 lead many economists and users of economic data to ask: How much worse, or better, might the economy perform than the baseline forecast? Moody’s Analytics provides guidance on this question via monthly updates of alternative scenarios. This article reviews how Moody’s Analytics calibrates, constructs and analyzes alternative scenarios for the U.S. economy and others around the globe. In doing so, two different kinds of econometric models are highlighted—structural and vector autoregression—that are used in the process of creating the alternatives. Further, this article describes the importance of a consistent narrative in the development of a scenario and the value of producing different scenarios based upon more than one narrative.

Baseline is starting point

The Moody’s Analytics monthly update of the baseline macroeconomic forecast is the starting point for the process of alternative scenarios. The process begins with a review by the chief economist and members of the research staff of the most recently available information on the U.S. economy, including high-frequency data releases, government policies enacted or proposed, and newly available topical studies.

The forecasting process employs the Moody’s Analytics U.S. macroeconomic model. This is a 1,500-equation structural model that is specified to reflect the interaction between aggregate demand and supply in the economy using equations that are statistically based links between the variables based on econometric regressions. For example, growth in real consumer spending per capita is a function of growth in real disposable income per capita as well as other factors. For a particular variable in the forecast, the approach is to weigh the importance of three time paths: 1) the previous month’s forecast; 2) the simple extrapolation of the recent trend in the variable; and 3) the results of the econometric equation.

Based on all this information, the chief economist directs the adjustment of the previous month’s forecast to reflect changes to historical data as well as changes in forecast assumptions. The result is, in Moody’s Analytics’ judgment, the mostly likely future outcome for the U.S. economy. However, since the chances of the economy exactly realizing any specific time path, no matter how reasonable, are small, the baseline is viewed as a boundary: There is a 50% probability that economic conditions will be worse and a corresponding 50% probability that economic conditions will be better during the current business cycle.

Monthly updates of the alternative scenarios follow the completion of the baseline outlook. Just as in the baseline, all of the alternative scenarios are based on current economic conditions. Therefore, the path of projected economic growth of a downside scenario during an expansion will appear stronger than an otherwise comparable downside scenario during a recession, just as the near-term baseline projection during an expansion period is stronger than the baseline in a recession.

Higher risk

Increased uncertainty in the economy in recent years has resulted in the monthly preparation of six alternative scenarios (see Chart 1). Previously, during the so-called Great Moderation and before the higher volatility associated with the Great Recession and its aftermath, only two alternative scenarios were prepared, one on the upside and one on the downside. Since the recession, downside scenarios have been produced with lower probabilities. In addition to the...
original probability of 1-in-4, downside scenarios with probabilities of 1-in-10 and 1-in-25 were added.

Like the baseline, these scenarios should be viewed as boundaries. For example, the 1-in-10 downside scenario is a borderline such that there is a 10% probability that the economy will perform worse and a 90% probability that it will perform better. There is also an upside scenario with a 1-in-10 probability that the economy will perform better.

The regularly updated scenarios always feature these particular probabilities because of their importance to users of the forecasts. For example, clients with a more pessimistic viewpoint have on some occasions used the 1-in-4 downside scenario as their baseline. Other clients, notably in the financial industry, have made use of the 1-in-25 downside scenario to evaluate the durability of their portfolios under economic conditions that would be far worse than expected.

**Consistent description**

A consistent economic narrative underpins each scenario. In other words, Moody’s Analytics posits specific factors or events that would push the economy away from baseline expectations. Since many possible events could produce the same downside outcomes for real GDP, the primary choices are those considered to be most likely under current economic conditions. For example, the main drivers for the downside scenarios include a worsening of the euro zone debt crisis, collapse of negotiations over U.S. deficit reduction, elevated gasoline prices eroding consumer confidence, and/or the return of a downward cycle in house prices as a result of more foreclosures than expected in the baseline forecast.

The production of several layered scenarios with essentially the same narrative and drivers provides the user the ability to measure the impact of the assumption of increased severity. The 1-in-10 downside scenario looks like the 1-in-4 downside scenario but with more pronounced changes from the baseline. Similarly, the contours of the 1-in-25 downside scenario look similar to those of the 1-in-10 downside scenario.

**Drivers**

In general, many possible economic drivers, or levers, need to be reviewed and sometimes adjusted to produce alternative scenarios. These include, among others, consumer confidence, fiscal and monetary policy, foreign economic growth, energy prices, expectations of default risk embodied in interest rate spreads, equity prices, the pace of consumer spending including vehicle sales, the pace of nonresidential or residential investment—including housing starts, inflation expectations and house prices—and the value of the dollar.

The approach is to begin with the fewest levers needed to produce a scenario, letting the structural equations in the model generate as much of the detail as possible. The results are then compared with past business cycles (see Chart 2). Further adjustments are then made so that a scenario is as consistent as possible with both past cycles and model-based results.

**Typically cyclical in nature**

In most scenarios, the focus is the short run. That is, with one exception to be described below, most are specified to provide an alternative view of when the current business cycle would end and the forecast would return to the baseline trend (see Chart 3). No further business cycles are assumed longer term, and long-run growth is equal to that in the baseline. The basis for this specification is the belief that uncertainty over the near term is higher than the uncertainty of the trend over the long run. This does not mean that Moody’s Analytics can do a better job of predicting GDP growth in, for example, 2023 than next year, but rather reflects the fact that the average annual pace of growth over many years has less volatility than growth in any one year.

**Multiple narratives**

During the current business cycle, a new dimension of uncertainty has emerged, namely disagreement over what might happen rather than how severe a decline might be, resulting in the creation of scenarios with alternative narratives. Specifically, until recently, the main downside scenarios have been essentially deflationary in nature, in that the drivers cause both output and inflation to decline in the near term. In contrast, the concern from some quarters is that near-term inflation is a greater risk. Advocates of this view point to the potential uncertainty.
for energy prices to rise on exacerbation of tensions in oil-producing countries and the enormous increase in the money supply in recent years as a result of quantitative easing to address the financial crisis. To reflect these views, Moody’s Analytics added an inflation scenario that posits rising oil prices, the emergence of accelerating inflation, an early policy response by the Federal Reserve, and, ultimately, a recession.

This alternative narrative results in variation in the timing of the cycle (see Chart 4). Whereas the main scenarios anticipate a downturn in the economy in the near term, the inflation scenario presumes that the contraction in the economy would follow the inflation phase and the Fed’s policy response. Consequently, the downturn in the inflation scenario is typically later than in the main scenarios by about nine months.

Further, the inflation scenario represents an example of an alternative whose probability is the same magnitude as that of one of the scenarios in the main narrative. Because it features a peak unemployment rate and cumulative decline in real GDP that are comparable to the 1-in-10 downside scenario of the main narrative, it, too, has a 1-in-10 probability (see Chart 5).

The only regularly updated noncyclical scenario is the result of a third narrative. Specifically, the current business cycle has featured an unusually slow recovery, an extended period of high unemployment, and unusually low consumer sentiment for a long time. Some observers believe that the duration is due to the fact that the damage to credit availability caused by the financial crisis will take an unusually long time to repair.²

Consequently, this scenario assumes that growth would remain below trend indefinitely because households would engage in more precautionary saving and less spending over the long term. The greater uncertainty about the future results in less risk-taking than in the baseline. Capital accumulation and productivity growth are lower than in the baseline, owing to the higher cost of borrowing and subsequently lower business investment. This scenario has a 1-in-25 probability because of the presumption that the below-average growth would extend for a full decade or more.

**VAR models**

The Moody’s Analytics approach to determining the particular alternative scenario associated with a particular probability involves the use of a vector autoregression model. Before describing this procedure, it is necessary to describe VARs and to contrast them with structural models.

A VAR model is a relatively small set of time series regressions with the specification that the only explanatory variables for each equation are the lagged values of the dependent variable itself and the lagged values of all the other variables in the model. In other words, the right-hand-side variables are exactly the same for each dependent, or left-hand-side, variable. VAR models are completely agnostic about structural linkages in the economy. For example, whereas many economists believe that the correlation between consumer spending and lagged disposable income should be positive, a VAR model that included these variables but featured one or more negative coefficients would be left as is.

Practical experience with the building of VARs has shown that typically no more than four lags are needed. The use of VARs in economic forecasting first began to grow in the early 1980s following research published by professor Christopher Sims, the 2011 Nobel laureate in economics.³ Since then, VARs have continued to be used for forecasting.⁴

However, Moody’s Analytics uses its structural model of the economy for several reasons. First, when the forecast is deemed inaccurate, it is easier to see where and why. Unlike a VAR, the structural model builds up the forecast of a major aggregate such as real GDP from its granular components, forecasting these components in terms of intuitive drivers. Therefore, if newly reported data on real GDP are deviating from the existing forecast, the deviation can be traced to the particular cause.

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For example, suppose the latest data on total real GDP are below what was previously projected and, upon examination of the model and data, the reason proves to be weak non-auto consumer durables such as furniture and appliances. In the model, this variable is a function of real disposable income per capita and household net worth in real estate, which in turn is correlated with house prices. In this hypothetical example, the weakness in real GDP growth could be traced to deeper-than-expected house price declines.

No such analysis is possible with a VAR model. The large number of required lagged variables on the right-hand side of the equations in a VAR force the model to be small, preventing the inclusion of important detail that a structural model can easily accommodate such as delinquency rates by type of liability, population by age cohort, energy prices, employment by industry, disaggregated consumer prices, housing permits and starts by category, house prices, or interest rates by asset class, among many other variables.

An analogy to how Moody’s Analytics predicts real GDP would be a company’s projection of expected earnings for the coming year. The chief financial officer would show that the company’s revenues were correlated with the major drivers of demand for the products of the industry as a whole and provide an analysis of how much demand was expected to grow during that time. There would follow an analysis of growth in costs of doing business. The forecast for net earnings would be a matter of arithmetic. But a company would be unlikely to brief stock analysts based on a VAR forecast of earnings.

A second problem with VARs is that the resulting forecast may be difficult to interpret. Imagine a VAR that included real GDP and payroll employment, in which the real GDP forecast was trending down while payroll employment was growing strongly. Since there is no structure, there is no explanation for why this might be occurring. Further, since the forecast would be counterintuitive, its reliability would be questionable.

Third, creation of meaningful alternative scenarios with a VAR has historically been problematic because no exogenous driver variables such as the price of oil were included in published models. However, such variables can be included, and the VAR that will be specified in this article includes some. Still, the problem remains that the results of such a shocked simulation could be counterintuitive.

Fourth, although proponents of VARs have insisted that their forecasts are more accurate than structural models, the jury remains out, and there is research to the contrary. Likewise, much-improved computer software has nullified the argument that VARs are quicker and easier to use.

**Monte Carlo simulations**

Returning to the discussion of alternative scenarios, there is one arena in which VAR models can be more useful than structural models. The uncertainty inherent in the estimated coefficients ("betas") and the disturbance terms of a VAR model can be translated into a range of alternative forecasts via Monte Carlo simulations. The distribution of these alternatives serves as guidance for assigning the probabilities of the Moody’s Analytics alternative scenarios. The approach is as follows.

The regression results for any model, structural or VAR, are statistical estimates of the true but unknown beta coefficients. As in the case of any other statistical estimate, there is a confidence interval around the estimated beta that is inversely proportional in size to its t-statistic. The higher the t-statistic, the tighter the confidence interval and vice versa.

To reflect the effect of this coefficient uncertainty, each estimated beta in the VAR can be replaced with another random choice from within the confidence interval. Once all the replacements have been made, the VAR can be resolved, resulting in an alternative forecast to the baseline. This process can be repeated indefinitely, each time resulting in an alternative forecast that is at least slightly different and in many cases significantly different from the baseline.

The distribution of these forecasts provides the information needed to assign probabilities to Moody’s Analytics alternative scenarios. For this purpose, the annual-average unemployment rate over a 10-year forecast horizon has been selected as the key measure, since it is a well-accepted barometer of overall macroeconomic activity and an important driver for many of the users of the forecasts.

**Details of the VAR**

The VAR used for the purpose of calibrating alternative scenarios includes all the major components of real GDP, allowing real GDP to be computed as an identity (see Table 1). Other variables included in the model are the consumer price index, the three-month Treasury bill rate, and the 10-year Treasury bond rate. Following testing, a lag length of three quarters was selected for all VAR variables. The estimation period was 1980Q4 through 2011Q4.

The output gap—measured as the gap between actual real GDP and the Congressional Budget Office’s measure of potential GDP—and the natural rate of unemployment are used to predict the actual rate of unemployment.

Specifically, the output gap is the factor that drives the deviation of the actual rate of unemployment from the natural rate of unemployment in a simple regression equation.

Besides potential GDP and the natural rate of unemployment, the price of oil, the exchange rate, and foreign economic activity were added as exogenous variables on the presumption that their levels are set by conditions outside the U.S. but that their levels affect U.S. economic activity. For the purpose of the VAR simulations, the future values of these exogenous variables were set equal to their forecast values in the March 2012 Moody’s Analytics U.S. macroeconomic baseline forecast.

The aim was to specify a VAR that would do a reasonably good job of predicting recent history subject to the desire to produce realistic Monte Carlo simulations.

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6 A Monte Carlo simulation is a method for iteratively evaluating a deterministic model using a random set of inputs. Such simulations are employed in the physical and social sciences to determine how random variation, lack of knowledge, or error affects the sensitivity, performance or reliability of the system that is being modeled.
This requires some explanation. As noted above, low t-statistics on beta coefficients equate to large confidence intervals. But a large confidence interval means that the alternative beta selected for the Monte Carlo simulations would frequently be far different from the estimated beta, and therefore the distribution of simulations would be unrealistically wide. Addressing this issue was straightforward. In each VAR equation, statistically insignificant lagged variables were dropped, and the model was re-estimated using Zellner’s Seemingly Unrelated Regressions (SUR) method, which assumes that the error terms are correlated across equations.

To see how well the resulting VAR predicted history, three separate simulations were run, beginning in 2007Q1, 2008Q1, and 2009Q1 (see Chart 6). As might be expected, the unprecedented depth of the Great Recession meant that model simulations using historical data up to 2007Q1 or 2008Q1 were not able to predict the downturn. However, the simulation using historical data up to 2009Q1 did somewhat better. Moreover, a slowdown in growth appears in all the forecasts and the unemployment rate rose in all cases (see Chart 7).

Next, the VAR was used to produce a forecast from 2012 to 2020. The result for real GDP was cumulatively slightly below the Moody’s Analytics baseline, with average annual growth 0.2% per year lower (see Chart 8). In general, the growth rate was slower through mid-decade and somewhat faster subsequently (see Chart 9). Further, the fact that the VAR unemployment rate forecast was higher than the baseline was consistent with its lower real GDP path (see Chart 10). Based upon all of the above, the results were in general judged to be reasonable.

### Calibrating alternative scenarios

The VAR model was then used to generate 10,000 Monte Carlo simulations running from 2012 through 2020. Only those in which real GDP was within one percentage point of potential GDP at the end point of the simulation were considered. This constraint is consistent with the observation that over a long time horizon, the U.S. economy has always returned to trend growth. This constraint reduced the number of simulations to about 1,000.

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**Table 1**

VAR Model Used to Calibrate Alternative Scenarios

<table>
<thead>
<tr>
<th>Endogenous variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>dlog(FCPIU.US)</td>
<td>Consumer price index</td>
</tr>
<tr>
<td>dlog(FC$.US/FPOP.US)</td>
<td>Total consumption expenditures (2005$) per capita</td>
</tr>
<tr>
<td>dlog(FI$.US/FPOP.US)</td>
<td>Total investment (2005$) per capita</td>
</tr>
<tr>
<td>dlog(FIM$.US/FPOP.US)</td>
<td>Total imports (2005$) per capita</td>
</tr>
<tr>
<td>d(FRTM3M.US)</td>
<td>Three-month Treasury bill rate</td>
</tr>
<tr>
<td>d(FRGT10Y.US)</td>
<td>Ten-year Treasury bond rate</td>
</tr>
<tr>
<td>FLBR.US-NAIRU_SR.US</td>
<td>Excess of unemployment rate over natural rate</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Exogenous variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>dlog(FCPWTI.US) *</td>
<td>Price of oil per ($/ barrel, West Texas Intermediate)</td>
</tr>
<tr>
<td>dlog(FTWDBRD$.US) *</td>
<td>Dollar exchange rate (weighted-average index)</td>
</tr>
<tr>
<td>dlog(FIMFWNGDPDUQ.IWRLD)</td>
<td>World GDP, bil $</td>
</tr>
<tr>
<td>POTGDP$.US</td>
<td>CBO estimate of potential real GDP</td>
</tr>
<tr>
<td>NAIRU_SR.US</td>
<td>Natural rate of unemployment</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Identities</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>FGDP$.US</td>
<td>Total GDP (2005$)</td>
</tr>
</tbody>
</table>

\[ d \log(x) - \log(x(-1)) \]

\[ d = x - x(-1) \]

* connotes three-quarter moving average

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**Chart 6: VAR Captured Part of Great Recession**

VAR historical simulations of real GDP by start date, $ tril

**Chart 7: Jobless Rate Rose in All Simulations**

VAR historical simulations of unemployment rate by start date, %

Sources: BEA, Moody’s Analytics
The mean of the distribution of average annual real GDP growth rates was about 2.4% per year, close to the average in the VAR baseline (see Chart 11). From these simulations, the annual average unemployment rate was calculated for each year of each simulation (see Chart 12). The full distribution includes years in which the economy is buoyant and unemployment is low as well as the opposite. This distribution allowed for a determination of the proportion of the years in which the unemployment rate would exceed a particular rate. These unemployment rates are broadly consistent with the peaks in the current Moody’s Analytics alternative scenarios (see Table 2).

Related U.S. forecasts

The alternative macroeconomic scenarios for the U.S. economy are used to create alternative scenarios for Moody’s Analytics regional forecasts, including all states and metro areas, the U.S. consumer forecast, the Case-Shiller house price index, and Credit-Forecast. For the state and metro area forecasts, adjustments that the analysts covering those geographies have made to the baseline forecast are carried through to the alternative scenarios. For example, if the analyst adjusted employment in a particular industry in the baseline forecast for a particular metro area based on specific information, that adjustment in industry employment would carry over to the alternative scenario, scaled to the divergence between national employment for that industry in the baseline and the alternative. However, this process is almost entirely mechanical for the state and metro area forecasts; analysts usually do not adjust the alternative scenarios for the states and metro areas they cover, unlike the baseline forecasts, which they adjust every month.

The same sort of approach is used to produce the Case-Shiller alternative scenarios, which are also available for all states and metro areas. The CreditForecast alternative scenarios are available for all states and 200 of the metro areas covered by the baseline forecast.

For the states, metro areas, U.S. consumer, and Case-Shiller forecasts, all of the alternative scenarios are produced every month. In contrast, CreditForecast.com is produced quarterly following data updates on credit conditions from Equifax. The alternative scenarios for CreditForecast.com are produced on this same quarterly schedule.

Custom scenarios for clients

Moody’s Analytics also produces custom alternative scenarios based on the client’s particular requirements. In some cases, the client supplies its own figures for key U.S. macroeconomic variables, which go into the structural model. The solution of the model then produces the full detailed forecast.
In most cases, the client’s variables will match up exactly with the same concept in the Moody’s Analytics forecast. In other cases, there may be slight definitional differences for a variable, and so the variable most similar to it in the model is adjusted to match up with the client’s forecast, usually using growth rates. For example, a client might provide a house-price variable that is similar to, but not exactly the same as, the median sales price for existing single-family homes from the National Association of Realtors. In that case, the NAR sales price forecast would be adjusted so that it grows at the same rate as the client’s variable. The client’s custom U.S. forecast can then be used to produce custom, client-specific state and metro area forecasts, similar to the process used to produce alternative state and metro area scenarios. Similarly, the custom U.S. forecast could be used to produce custom U.S. consumer forecasts, Case-Shiller home price index forecasts, and CreditForecast.

**Conclusion**

Moody’s Analytics has responded to increased macroeconomic uncertainty in recent years by expanding its offerings of alternative scenarios. More scenarios with lower probabilities are prepared and regularly updated, as are scenarios with alternative narratives. The most recent addition is regularly updated scenarios for other countries.
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Edward Friedman is a director at Moody's Analytics. Dr. Friedman prepares alternative macroeconomic forecasts for the Moody's Analytics baseline utilizing the 1,500-equation macroeconomic model, edits monthly regional and macroeconomic publications, produces forecasts for Texas and its major metropolitan areas, writes monthly summaries of the U.S. financial industry, and supervises a project to expand metropolitan area forecasting to foreign cities. He previously worked for the Federal Reserve Bank of New York, supervising the collection of data on cross-border transactions in securities. Dr. Friedman received a PhD in international economics from Yale University. His bachelor’s degree in mathematics is from Dartmouth College.

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About Moody's Analytics
Economic & Consumer Credit Analytics

Moody's Analytics helps capital markets and credit risk management professionals worldwide respond to an evolving marketplace with confidence. Through its team of economists, Moody's Analytics is a leading independent provider of data, analysis, modeling and forecasts on national and regional economies, financial markets, and credit risk.

Moody's Analytics tracks and analyzes trends in consumer credit and spending, output and income, mortgage activity, population, central bank behavior, and prices. Our customized models, concise and timely reports, and one of the largest assembled financial, economic and demographic databases support firms and policymakers in strategic planning, product and sales forecasting, credit risk and sensitivity management, and investment research. Our customers include multinational corporations, governments at all levels, central banks and financial regulators, retailers, mutual funds, financial institutions, utilities, residential and commercial real estate firms, insurance companies, and professional investors.

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Moody's Analytics added Economy.com to its portfolio in 2005. Its economics and consumer credit analytics arm is based in West Chester PA, a suburb of Philadelphia, with offices in London and Sydney. More information is available at www.economy.com.