Moody’s Analytics Global Macroeconomic Model Methodology

INTRODUCTION

Economic models are valuable tools for prediction, understanding and analysis of data. The key challenge in macroeconomic modeling—the one that sets the task apart from other types of modeling—is to posit a clear, limited set of causal relationships to ensure a stable, tractable model while still mirroring a real-world environment where “everything affects everything.” In the modern global economy, the scale of this conundrum of causality is magnified greatly. Meeting client needs for internationally consistent macroeconomic forecasts, along with reasonable and supportable alternative scenarios to satisfy regulators, requires a judicious approach informed by a careful balance of economic theory, empirical evidence and diagnostic testing.
Moody’s Analytics Global Macroeconomic Model Methodology

BY MARK HOPKINS

Economic models are valuable tools for prediction, understanding and analysis of data. The key challenge in macroeconomic modeling—the one that sets the task apart from other types of modeling—is to posit a clear, limited set of causal relationships to ensure a stable, tractable model while still mirroring a real-world environment where “everything affects everything.” In the modern global economy, the scale of this conundrum of causality is magnified greatly. Meeting client needs for internationally consistent macroeconomic forecasts, along with reasonable and supportable alternative scenarios to satisfy regulators, requires a judicious approach informed by a careful balance of economic theory, empirical evidence and diagnostic testing.

In this context, the Moody’s Analytics Global Macroeconomic Model produces interrelated forecast paths for more than 16,000 macroeconomic time series spanning 73 countries that together account for more than 97% of the world’s output (see Chart 1). Another 31 emerging market economies are forecast in a satellite model driven by those global model forecasts. The GMM is a structural model, consisting of a single, large system of simultaneous equations. It reflects some specific economic relationships, with cross-country interactions introduced through various demand, price and financial market linkages across those equations. A baseline and 10 standard alternative scenario forecasts are produced at a quarterly frequency, over a 30-year time horizon. These are updated monthly to retain consistency with the most recent available economic data.

In addition to producing detailed forecasts for individual countries, the GMM reports key concepts for a number of country aggregates. These include geographical regions (for example, South America, Europe), major institutional groupings such as the EU and the euro zone, and in some cases breakdowns by income (developing versus developed Asia, for instance). Throughout the global model, Moody’s Analytics employs a “top-down, bottom-up” methodology. Global growth projections are constructed from a huge array of forecasts for consumption spending, investment and trade across individual countries. These building blocks depend in turn on a set of global drivers and various “high level targets” that can be adjusted by the model user to produce alternative forecast paths quickly and efficiently across thousands of global series.

Modeling alternatives and choices

The GMM is a tool that allows users to design their own global forecasts. The model aggregates a vast array of international economic data, mapping the information to a set of predicted paths for various concepts of interest. The model is not a crystal ball, however. When solved, its equations produce expected values conditional on a set of model parameters and assumptions. The model was designed with multiple points of entry, where users can alter those assumptions as desired.
Clients can use the GMM to predict future values of key economic time series such as GDP, interest rates and inflation; produce counterfactual scenario projections of those variables under varying sets of assumptions; or simply facilitate their understanding of these outcomes by tracing the path of “cause and effect” as shocks propagate throughout the global economy.

In this sense, models are tools and, as with all projects, the best tool always depends on the nature of the job. Macroeconomic models are typically employed for one of three main purposes: baseline forecasting, scenario evaluation and economic insight. However, an economic model that is superior in producing out-of-sample forecasts may do poorly in evaluating the impact of alternative assumptions, like predicting the impact of a tax cut on spending or of a depreciation of the exchange rate on investment spending. Another modeling approach might do well generating alternative scenarios, but act too much as a “black box,” providing little transparency into the results and preventing the model user from justifying its predictions to others.

At the heart of the Moody’s Analytics forecasting methodology is a recognition that a bespoke model built to answer a specific question will generally be superior in each case, but such a model can never be superior in all cases. Yet, there are cost considerations—as well as clients’ desire for consistency and transparency in our analysis and results, and regulators’ desire for methodological clarity, uniformity and process governance. These create a need for baseline and scenario predictions made using a single, flexible, transparent and heavily vetted macroeconomic forecasting model. While specialized “satellite models” can be usefully employed to calibrate appropriate model inputs, forecast benchmarks or scenario targets, all country forecasts published by Moody’s Analytics are constructed using this single, unified, structural model, following the methodology laid out in this document.

Accordingly, this model is constructed to accommodate and balance a wide array of objectives and competing trade-offs, including:

» **Conditional accuracy.** Forecasts should not simply be correct, but also internally consistent. Interest rates, inflation rates, and GDP growth paths are forecast jointly, not independently. A poor prediction need not invalidate the model as long as the equation input, rather than the equation itself, is to blame.

» **Stability.** Left alone, forecasts for stationary time series should revert to their long-run “anchors” and the model should not crash easily when shocked.

» **Dynamic properties.** The time paths of key variables should be consistent with stylized facts, textbook theory and empirical evidence (for example, match empirical impulse response functions).

» **Business productivity.** Model users should be able to tune a baseline forecast or generate an alternative scenario forecast quickly and easily, by tweaking a few key series.

» **Flexibility.** The model must be suitable for multiple business purposes, including being able to run both “forward,” for traditional forecasting, and “in reverse,” for regulatory stress-testing. For example, the model must be able to produce a forecast for GDP given information on consumer spending and the trade balance, or a prediction for consumer spending and the trade balance given regulatory guidance on GDP.

» **Theoretical support.** Model equation specifications must all be justifiable, supported either by macroeconomic theory or well-understood empirical relationships.

» **Predictive power.** The model should produce a reasonably accurate baseline forecast, in the absence of any model user adjustments.

» **Counterfactuals.** The model should have the ability to simulate the impact of discrete “policy shocks” well, both qualitatively and in appropriate magnitude, including the propagation of shocks throughout both the domestic economy and the broader global economy.

**Five principles for the global model**

To confront the many methodological trade-offs and to optimize over the multiple objectives, the global model was created by adhering to five key principles.

**Principle 1:** Build in key tuning parameters for command and control.

Like an aircraft carrier, the global model is huge and could easily become unwieldy unless designed specifically to be operated efficiently, and even single-handedly. To this end, the model is built around a handful of key drivers or “tuning variables” that are endogenous yet play the role of exogenous drivers in much of the model. One example of these tuning variables are the inputs employed in the “top-down, bottom-up” structure. Other inputs are simply important variables by their nature, like oil prices or the federal funds rate, which have an outsize effect on the rest of the model, either directly or indirectly.

**Principle 2:** Key macroeconomic variables all have long-run anchors set by either supply-side assumptions or by long-run equilibrium relationships (see Table 1).

**Principle 3:** The global model should have some adjustment mechanism built into every country by which all variables will converge to their long-run anchors.

There are several convergence mechanisms built into the model. One type acts through a single equation, by the inclusion of a mean-reversion or error-correction term in which the growth rate of a series is negatively related to its deviation from equilibrium.

A second type of convergence mechanism acts across multiple equations. These are
largely representations of the standard macroeconomic consensus theory. Consider, for example, the impact of a sudden increase in GDP. The model will generate the following responses (with the associated theoretical mechanism given in parentheses):

» The unemployment rate will fall (Okun’s law);

» The inflation rate will rise (the Phillips curve);

» Short-term interest rates will move higher (Taylor rule);

» Long-run interest rates will move higher (term structure of interest rates);

» Real exchange rates will move higher (interest rate parity);

» Real net exports will decline with their higher cost abroad (demand curve), and

» Real GDP will decline (the NIPA identity), eventually bringing output back into equilibrium with the level of potential output.1

Principle 4: The global model should have desirable “shock properties.”

To meet the demands of financial risk mitigation, including regulatory stress-testing and expected loss accounting, the global model needs to be able to produce a wide array of reasonable and supportable alternate scenarios. However, the sensitivity to changed assumptions required for the model to produce clearly divergent alternative paths must be weighed against the need for stability in the solution and a robust baseline forecast that will not jump around confusingly from month to month as new historical information is incorporated. The goals of sensitivity and stability necessarily conflict to some degree, but an optimal balance can be struck by taking care in model design.

Specifically, for the model to display simultaneously short-run sensitivity to shocks but long-run stability and forecast invariance, several technical conditions must be met. First, the model must also have short-term positive feedback mechanisms so that shocks propagate through the model to deliver deviations from the baseline of appropriate magnitude to a range of variables. For instance, a fall in spending triggers a fall in income and wealth that triggers a bigger decline in spending. These positive feedback “shock mechanisms” must operate strongly on a short-term time horizon, so they dominate the impact of any other effects over the first one to six quarters.

At the same time, these short-term positive feedback shock mechanisms must die out quickly, so that over the long run (five to 20 quarters) the negative feedback adjustment mechanisms described in Principle 3 come to dominate. Otherwise, any shock to the model will persist for too long or even explode outward, never returning to the baseline, or simply producing too much volatility and instability in the forecast.

Principle 5: Ensuring the competing goals of positive feedback mechanisms dominating in the short run and negative feedback dominating in the long run requires equations that achieve balance along two dimensions: coefficient magnitudes and decay parameters (see Box 1).

Table 1: Key Forecast Variables Tied to Equilibrium Anchors in Long Run

<table>
<thead>
<tr>
<th>Variable</th>
<th>Long-run anchor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment rate</td>
<td>Equilibrium rate of unemployment (NAIRU)</td>
</tr>
<tr>
<td>Labor force</td>
<td>Trend labor force participation rate * population ages 15-64</td>
</tr>
<tr>
<td>Real GDP</td>
<td>Potential output level</td>
</tr>
<tr>
<td>CPI inflation rate</td>
<td>Central bank inflation target</td>
</tr>
<tr>
<td>Interest rates</td>
<td>Nominal potential GDP growth rate</td>
</tr>
<tr>
<td>Exchange rate (LC/USD)</td>
<td>Relative CPI (that is, purchasing power parity)</td>
</tr>
</tbody>
</table>

Source: Moody’s Analytics

1 For this to work in level form, rather than the usual way in terms of growth rates and changes in unemployment, Okun’s law has to be expressed in log levels of GDP and the level of unemployment, using the natural rate from the Phillips curve as the undefined constant.

Taking theory to the data

Economists continue to enjoy spirited methodological debates over the best way to model the economy and the wide array of approaches employed. Each has its defenders. However, over the last few decades, macroeconomic theory has evolved toward a consensus view best described as “Keynesian in the short run, and classical in the long run.” This is reflected in the following empirical relationship between growth in output and prices and the rate of interest:

» Output (GDP) depends on spending, which is determined by the expected real rate of interest, or the nominal interest rate less future inflation;

» Nominal interest rates are determined partly by monetary policy interventions but also by demand for credit, which is influenced by current activity (GDP) and expected inflation, and

» Inflation reflects the choices made by firms when setting prices, but these choices depend on the level of real activity and inflationary expectations.

Mathematically, these three unknowns—real GDP, nominal interest rates, and inflation—can be solved in a system of three equations, conditional on a set of given expectations of future income and inflation.

The classical long run is achieved at the point where expectations are consistent with reality—where activity and prices remain stable at equilibrium values governed entirely by the supply side of the economy. Real GDP converges to its potential level, which is dictated by demographics, participation preferences and productivity; inflation is stable at its expected rate, and interest rates converge to a level consistent with long-run nominal GDP growth and liquidity preferences.

In the short run, however, a shock to any part of this system can cause spending and
Box 1: Balancing Coefficient Magnitudes and Decay Rates in Equation Specifications

Consider a simple model with three variables: X, Y and Z. Specifically, assume Y=GDP, which depends positively on two drivers X (investment) and Z (the price of foreign exchange). All three variables demonstrate persistence in the form of a lagged dependent variable. In addition, the model has two feedback mechanisms: An increase in Y increases X in the next period (positive feedback) but also lowers Z in the next period (negative feedback).

\[
\begin{align*}
Y_t &= aY_{t-1} + bX_t + cZ_t + \varepsilon \\
X_t &= \rho X_{t-1} + dY_{t-1} \\
Z_t &= \rho Z_{t-1} - fY_{t-1}
\end{align*}
\]

For the model to meet the dual goals of (1) long-run stability, with Y converging to trend eventually, and (2) short-run shock properties, we would need the following conditions to hold:

| \(\rho_X\) | Small (close to 0) |
| \(\rho_Z\) | Big (close to 1) |
| \(b\)     | Big               |
| \(c\)     | Small             |

In this case, a positive shock to GDP (\(\varepsilon\)) would have three effects:

1. It would persist naturally through the AR(1) term for GDP (\(a\)), absent any feedback mechanisms to other variables in the model.
2. It would increase future values of X, which would have a large effect initially, pushing up Y even further. But this effect through X would die out relatively quickly because of the small AR(1) coefficient on X.
3. It would decrease future values of Z, which would have only a moderate effect in reducing Y in the future, though this effect would persist for a relatively long time.

inflation to depart from expectations. When this happens, GDP, interest and inflation rates accordingly will depart from their long-run levels, giving rise to the familiar dynamics of the business cycle.

Econometrically, this balance of Keynesian dynamics in the short run with Classical equilibrium convergence in the long-run is achieved by exploiting an error-correction type framework in which short-run changes in one variable are tied both to short-run changes in other variables and in the deviation in levels of those variables. The first effect drives centrifugal forces in the model, generating standard business cyclical responses to shocks to spending, prices, or financial market variables. The second effect creates the centripetal force that gradually brings the economy back to its long-run equilibrium.

The fundamental difficulty in operationalizing the consensus theory within an empirical, computational model is the centrality of expectations in the story. Expectations are difficult to quantify, let alone to predict. This difficulty has given rise to three distinct modeling approaches, all in common use today:

» At one end of the spectrum are pure time-series methods that require few, if any, assumptions from economic theory. These methods rely on highly flexible, reduced form specifications that "let the data speak."

» On the opposite end are models built upon equations specifying mathematical solutions to a set of optimization problems in microeconomic theory. By imposing these strong assumptions upon the data, these models seek to uncover hidden truths rather than trying simply to "fit" the data we observe.

» In the middle of these extremes, governed equally by relationships support-
A common example of the time-series approach to forecasting is the vector autoregressive model. Rather than using theory to specify an assumed structural relationship between GDP, interest rates and inflation rates, each variable in a VAR is regressed on past values of all others; no attempt is made to impose, or to infer any type of causal explanation for the correlation, nor do the individual coefficients have any economically meaningful interpretation. Theoretical restrictions are necessary only when trying to infer causal effects from shocks, not for prediction.

The greatest advantage of this approach is its dispensing with the need for economic theory and relating instead on observable historical covariation, VARs are largely immune from criticisms that they are "mis-specified." The flexibility from the high degree of parameterization also results in fairly accurate forecasts over short time horizons. As additional theoretical restrictions are imposed, they can also help predict the dynamic responses of variables, or "impulse responses" under alternative scenarios. However, the VAR method suffers from at least three important limitations:

1. First, the forecasts are difficult to explain. The lack of theory and large number of regressors makes the model largely a black box. Second, the high degree of parameterization in a VAR both reduces the efficiency of the resulting estimates, and limits the scope of variables that can be forecast practically. A typical VAR is built to incorporate from two to 10 variables, providing a limited view of the economy compared with the more than 1,000 forecast in the Moody's Analytics U.S. macro model. Finally, prioritizing past experience over theory makes VARs less capable of incorporating possibilities outside the scope of experience. (for example, "black swan" events).

2. Two examples of the second, more theoretical, "micro-foundations" approach include deterministic real business cycle models and the increasingly popular dynamic stochastic general equilibrium, or DSGE, model. In both cases, equations are derived from equilibrium expressions for the aggregate outcomes of consumption, investment, and other activities, allowing individual forward-looking optimizing behavior across a multitude of consumers and firms. These models are theoretically elegant, allowing individual forward-looking behavior: the model is solved through the iterative convergence of agent actions, outcomes and expectations in a way that are all mutually consistent.

The incorporation of micro-foundations and rational expectations comes at a high computational cost, however. This limits their practical value, since it is cumbersome to include more than a handful of variables, or, with a DSGE: Deriving tractable model solutions also requires strong assumptions (for example, all consumers and firms are identical with specific, simple preferences and information technologies). As a result, DSGEs remain most popular within academic circles, where the value of the model predictions is less than the elegance of the theoretical, with a DSGE. Deriving tractable model solutions is a formidable task. While VARs can achieve. At the same time, structural macroeconomic models do not rely on some of the extreme, often unrealistic assumptions that make DSGEs susceptible to misspecification or constraint their explanatory scope.

The third approach offers a versatile and powerful alternative. Despite their great flexibility from the high degree of parameterization, VARs are largely immune from the stability of the entire system. Indeed, the notion that such models are in fact "structural" at all was challenged famously by Nobel laureate Robert Lucas, who argued that most economic relationships are not "structural" in the economy—even well-known, empirically validated relationships such as the Phillips curve relationship between inflation and unemployment should not be assumed to be constant and invariant to changes in the rest of the economy.

This approach is not without some costs, of course. Because of the mutual dependency of so many variables, much care is needed when specifying and estimating equations, to ensure both the validity of the coefficient estimates as causal relationships and the stability of the entire system. Indeed, the notion that such models are "structural" at all was challenged famously by Nobel laureate Robert Lucas, who argued that most economic relationships are not "structural" in the economy—even well-known, empirically validated relationships such as the Phillips curve relationship between inflation and unemployment—should not be assumed to be constant and invariant to changes in the rest of the economy.

Chart 2: Structural Model Methodology

Source: Moody's Analytics
In a sense, his critique was to remind economists that "correlation need not imply causation."

In response, Moody's Analytics, like many forecasters employing these models, often relies more heavily on exogenous forecasts to stabilize in the forecast process. The reduction in simultaneous variables or proxy instruments in the place of direct contemporaneous correlations to reduce problems of endogeneity bias in estimation. The reduction in simultaneous dependence also aids with solver speed and stability in the forecast process.

In further contrast to VARs and DSGEs, structural macroeconomic models typically rely more heavily on exogenous forecasts and assumptions introduced from outside the model. Examples include demographic projections, assumptions regarding production, productivity growth, fiscal and monetary policy actions, and economic activity outside of the U.S. These assumptions allow forecasters to incorporate information that is known, but not internal to the model; far more easily than in VARs and DSGEs.

Where structural macroeconomic models truly excel, however, is in exploring the implications of alternative assumptions regarding some variables on others, such as those used in stress-testing exercises. In regulatory stress-testing, financial institutions are tasked with estimating portfolio loss under a small, prescribed set of macroeconomic assumptions. But rarely do bank balance sheets depend precisely on these broad macroeconomic assumptions.

Differences in macro models

As a large, simultaneous system of non-linear differential equations, the global model must be able to produce forecasts for a large set of time series within a single solution. The model must be cohesive, sensible, dynamically stable as a system, and not just a random collection of equations that are justifiable on their own but not reciprocal or contradictory when used in combination. The most crucial concept in any macroeconomic forecasting exercise is causality.

In this context, it is important to understand the differences between the country models used by Moody's Analytics and the many other types of models employed in business and academia. Most important is the idea that our global model does not simply produce forecasts, but is a platform that allows users to construct a variety of scenarios. Almost all models by academics, and most of those used by financial corporations, are purpose-built, and as a result there is little or no role for the model user. The user inputs all available information, but is a passive recipient of the model's output. There is no additional insight the user can provide, or can glean from the output, beyond the forecast the model produces. This stands in stark contrast to a structural macroeconomic model, which serves as an analytical tool more akin to an accountant's calculator than a mystical oracle emitting prophecies amid a cloud of vapors.

But rarely do bank balance sheets depend precisely on these broad macroeconomic assumptions. The quality of the degree of equation fit for loan losses is consistency in the direction of causality across equations.

In reality, almost everything in the economy depends on everything else; however, in the stylized world of statistical models, establishing assumptions of causality is critical to building a structural model. If credit losses depend positively on unemployment and unemployment depends positively on credit losses, the system can become unstable. More important, the stronger these relationships appear (the larger the t-statistics and better the fit of the model), the more this threat of explosive instability becomes.

For this reason, as discussed in this document, the methodological considerations around choice of equation specification, estimation strategies and diagnostic testing all differ from those that might be used in alternative contexts, such as simple time series forecasting or credit loss modeling. In particular, the roles of a priori theory, consistency of causal ordering across equations, and the accuracy of the resulting model simulation in practice are all given much greater weight relative to the values of standard econometric equation hypothesis tests. Measures of equation fit, coefficient significance, and residual serial correlation are still valuable, but for their diagnostic value rather than in providing meaningful statistical inference under a well-defined null hypothesis.
The country structure in the global model

Moody’s Analytics employs the same forecasting methodology in building all of our country models, but the specific linkages across the model equations and the exact functional form used in the econometric specification typically vary from country to country. Initially, every country model is estimated according to a standard template; however, this template is flexible, allowing for differences for countries with fixed versus floating exchange rates, or net energy exporters versus importers, for example.

Once initial estimation is complete, equations are then inspected, tested, evaluated, and changed as necessary to optimize baseline forecast accuracy and scenario shock responses. In general, equations differ across countries for three principal reasons: data availability, the composition of industry and exports in that country, and differences in historical experience that negatively affect the signs and significance of key right hand side variables. The exact criteria used in the evaluation of what constitutes an acceptable equation are discussed below. In general, however, an equation is judged to be acceptable if it has coefficients that produce a reasonable, accurate baseline forecast without human intervention, and which generate appropriate shock responses in scenario tests.

In keeping with earlier discussion of structural versus reduced form modeling, most equations are specified as functions of a known set of covariates up to some unknown parameters, the values of which are estimated based on a least squares fit of the model equation to historical data. Most of these functions are linear or log linear representations, with specifications guided by mainstream macroeconomic literature. A brief description of the base specifications used in the initial model estimation for each country is given in Appendix 1.

Cross-country linkages

Conceptually, the global model consists of 64 different country-level macroeconomic models, all tied together through a specific set of cross-country linkages of the following types:

- Trade linkages. Exports are tied to a trade-weighted average of the imports of the exporter’s five largest export markets. Imports also depend on the real effective exchange rate, which depends on foreign prices and exchange rates.

- Financial linkages. Among those countries with liberal current accounts and convertible currencies, global financial arbitrage activity exercises a strong impact on domestic interest rates, equity prices, and exchange rates. In particular, while short-maturity interest rates are driven largely by central bank policy, longer maturity bond yields in convertible currencies are linked through uncovered interest rate parity to a global benchmark rate, proxying the U.S. Treasury yield.

Equation specification

The Moody’s Analytics global macro model is a structural model. This means each equation is specified and not merely estimated; it contains its own productive value, but also to abide by textbook macroeconomic theory. Wherever possible, theory is applied strictly with the specific functional forms motivated in the first order instead of some optimization problem, and with the equation parameters having a clear structural interpretation. In other cases, theory is applied more broadly by directly employing the first order Taylor rule rule expansions to generate log-linear...
In specifying and estimating these equations, a few instances of “world prices” (or interest rates or GDP growth) in the simultaneous core of one country would actually imply the addition of many thousands of variables in the core, slowing convergence times considerably. For this reason, the model often uses just a given value for the U.S., and/or another large regional economic powerhouse such as the euro zone, Japan, or China as a proxy for the equivalent global aggregate concept. Either the U.S. CPI is used in place of “global prices” as a driver for a country’s export and import price deflators, the U.S. Standard & Poor’s 500 stock market index is used as a proxy for average global stock prices, and the U.S. Treasury yield curve is used as a proxy for the maturity spread on global risk-free debt, over which foreign yields are marked up/down in line with their domestic monetary policies and perceived default risks.

Top-down vs. bottom-up in theory, French GDP is the sum of final goods market expenditure in France, and euro zone GDP is the sum of GDP across all of the euro zone countries. However, investment in France may be determined in part by growth in euro zone GDP. In theory, a model solution may be computed with a consistent path for French investment given euro zone GDP and euro zone GDP given French investment, but a large number of iterations may be required.

**Chart 3: “Top-Down” and “Bottom-Up”**
Econometric estimation

Almost all model parameters are estimated econometrically rather than calibrated. Those which are calibrated are done so as part of a transformation of the dependent variable—for instance, if $Y$ depends on $X$ and $Z$ and we know the coefficient on $X$ should be 0.5, the coefficient on $Z$ would be estimated through a regression of $(Y - 0.5X)$ on $Z$. In performing econometric estimation, one parameter (a proxy variable with longer history) is often used to reduce the bias vs. variance trade-off. For example: (1) introducing bias from omitted relevant variables versus increasing variance (and thus parameter instability from excessive multicollinearity) by including extraneous variables, and (2) removing potential endogeneity bias through use of instrumental variables (a 2SLS estimator) versus increasing parameter (and forecast) variance relative to the more efficient OLS method.

Once these initial template equations are estimated, the results are scrutinized by the modeler but are not determined, which then drives lower-level forecasts, which are summed to produce an aggregate that mirrors, if not exactly equals, the initial forecast (see Chart 3). Examples of top-down/bottom-up specifications are in Appendix 2.

Examples include (but are not limited to): (1) introducing bias from omitted relevant variables versus increasing variance (and thus parameter instability from excessive multicollinearity) by including extraneous variables, and (2) removing potential endogeneity bias through use of instrumental variables (a 2SLS estimator) versus increasing parameter (and forecast) variance relative to the more efficient OLS method.

Once these initial template equations are estimated, the results are scrutinized by the global modeling team to ensure all parameters have the correct sign and reasonable significance, the equation fit is sufficient, and the estimation sample is large enough to ensure robust and stable coefficient estimates as model history is updated over time. In the case of overall good equations with a specific problematic coefficient, small permutations of the variable are tested, including alternate lag structures, moving averages (to improve the signal/noise ratio), and transformations. Variables are specified in levels to one in differences, as appropriate.

Unfortunately, trying to reduce either bias or variance often comes at the expense of increasing the other. For this reason, all choices of equation specifications and estimation methods are done with a (subjective) view of what the modeler believes optimizes the bias vs. variance trade-off, and the t-statistic is important largely for determining how strong an effect each variable relative will have relative to others when shocked during scenarios. For example, a much larger t-statistic on interest rates than stock prices in an investment equation implies that an analogous shock to interest rates will have a much more strongly to a one-standard deviation shock to interest rates than it would to an analogous shock to stock prices.

The $R^2$ of an equation measures the equation "fit," or the share of the variance in the dependent variable that can be explained by the regression equation. In backward-looking analytical use, the $R^2$ can be used as a proxy for the probability of a given specification being "correct," under the notion that the best theory is that which can best match historical patterns. In the forecasting context, again, adherence to theory is considered more important than model fit in selecting a final equation specification. Nevertheless, the resulting $R^2$ is an important indicator of the degree to which the dependent variable will...
The Durbin-Watson test statistic is useful for its standard role in revealing the presence of serial correlation in the residuals. In both standard and backward-looking analytical and forward-looking forecasting applications, it is important to know if the residuals are predictable and thus contain some information that is not being exploited. In the case of structural models, this is of less concern because the goal is to link forecasts for variables to other variables rather than to stochastic error terms. However, a DW value that departs from 2 indicates that a variable is likely to display a “first forecast quarter jump-off” problem, since the expected value of the residual, conditional on a previous history, is not zero. This issue is typically addressed as part of the monthly line-up process.

Although not desirable, the presence of residual serial correlation is often considered acceptable in structural models because the standard remedy, ARMA modeling of the error term, frequently entails more cost than benefit in terms of the forecast. This is because many structural relationships are based on long-run equilibrium conditions, not short-run causal relationships, and for this reason the residuals display a high degree of persistence. Including an autoregressive term to correct for this is likely to lead to an autoregressive coefficient close to 1, with an accompanying large loss in significance in the desired covariates in the structural equation. An easy example would be stock prices. In theory, stock prices are tied to corporate earnings per share and interest rates. But in the short run, stock prices behave much like a random walk. As a result, the residuals in a stock price equation may display considerable serial correlation. Inclusion of an AR term eliminates serial correlation and “improves” the DW statistic, but in doing so the AR error absorbs nearly all of the variation, rendering insignificant the coefficients on earnings and interest rates. In a scenario forecasting context, if GDP and interest rates in the resulting model were shocked, there would be almost no impact on stock prices.

Equation stability.

- Equations modeled in levels with no lagged dependencies will suffer “jump-off problems.”
- Equations modeled in changes (percent change or differences) may suffer from stability problems, need anchors, or ECM specifications to ensure stability.
- Equations modeled in four-quarter changes should be avoided—shocks propagate forward as undesired “cyclical.”

Causation vs. correlation.

- Lag or instrumental variables should be used where OLS estimates may be improperly estimated (that is, not reflect true causal relationships).

Short vs. long regressions.

- Equation specifications should trade off the following three desired criteria:
  - Parsimony. Variables should be excluded that have a low signal/noise ratio (low t-statistics), to ensure stability and accuracy of forecasts.
  - Shockability. Equations should have sufficient mechanisms built in to allow interesting and appropriate shock propagation to generate scenarios.

Although not desirable, the presence of residual serial correlation is often considered acceptable in structural models because the standard remedy, ARMA modeling of the error term, frequently entails more cost than benefit in terms of the forecast. This is because many structural relationships are based on long-run equilibrium conditions, not short-run causal relationships, and for this reason the residuals display a high degree of persistence. Including an autoregressive term to correct for this is likely to lead to an autoregressive coefficient close to 1, with an accompanying large loss in significance in the desired covariates in the structural equation. An easy example would be stock prices. In theory, stock prices are tied to corporate earnings per share and interest rates. But in the short run, stock prices behave much like a random walk. As a result, the residuals in a stock price equation may display considerable serial correlation. Inclusion of an AR term eliminates serial correlation and “improves” the DW statistic, but in doing so the AR error absorbs nearly all of the variation, rendering insignificant the coefficients on earnings and interest rates. In a scenario forecasting context, if GDP and interest rates in the resulting model were shocked, there would be almost no impact on stock prices.

Equation stability.

- Equations modeled in levels with no lagged dependencies will suffer “jump-off problems.”
- Equations modeled in changes (percent change or differences) may suffer from stability problems, need anchors, or ECM specifications to ensure stability.
- Equations modeled in four-quarter changes should be avoided—shocks propagate forward as undesired “cyclical.”

Causation vs. correlation.

- Lag or instrumental variables should be used where OLS estimates may be improperly estimated (that is, not reflect true causal relationships).

Short vs. long regressions.

- Equation specifications should trade off the following three desired criteria:
  - Parsimony. Variables should be excluded that have a low signal/noise ratio (low t-statistics), to ensure stability and accuracy of forecasts.
  - Shockability. Equations should have sufficient mechanisms built in to allow interesting and appropriate shock propagation to generate scenarios.

Although not desirable, the presence of residual serial correlation is often considered acceptable in structural models because the standard remedy, ARMA modeling of the error term, frequently entails more cost than benefit in terms of the forecast. This is because many structural relationships are based on long-run equilibrium conditions, not short-run causal relationships, and for this reason the residuals display a high degree of persistence. Including an autoregressive term to correct for this is likely to lead to an autoregressive coefficient close to 1, with an accompanying large loss in significance in the desired covariates in the structural equation. An easy example would be stock prices. In theory, stock prices are tied to corporate earnings per share and interest rates. But in the short run, stock prices behave much like a random walk. As a result, the residuals in a stock price equation may display considerable serial correlation. Inclusion of an AR term eliminates serial correlation and “improves” the DW statistic, but in doing so the AR error absorbs nearly all of the variation, rendering insignificant the coefficients on earnings and interest rates. In a scenario forecasting context, if GDP and interest rates in the resulting model were shocked, there would be almost no impact on stock prices.

Equation stability.

- Equations modeled in levels with no lagged dependencies will suffer “jump-off problems.”
- Equations modeled in changes (percent change or differences) may suffer from stability problems, need anchors, or ECM specifications to ensure stability.
- Equations modeled in four-quarter changes should be avoided—shocks propagate forward as undesired “cyclical.”

Causation vs. correlation.

- Lag or instrumental variables should be used where OLS estimates may be improperly estimated (that is, not reflect true causal relationships).

Short vs. long regressions.

- Equation specifications should trade off the following three desired criteria:
  - Parsimony. Variables should be excluded that have a low signal/noise ratio (low t-statistics), to ensure stability and accuracy of forecasts.
  - Shockability. Equations should have sufficient mechanisms built in to allow interesting and appropriate shock propagation to generate scenarios.
The forecast process

Historical data and model baseline forecasts are updated in the second week of each month. A team of trained economists reviews the baselines and adjusts the baseline forecasts, reflecting new qualitative information, such as shifts in expectations.
a central bank’s monetary policy stance, changes in market sentiment, or newly released government budget documents and business surveys.

The baseline forecast is produced according to the following steps:

» History is updated with new data for endogenous variables.

» All existing add-factors are cleared out, and then recalculated to preserve the previous forecast path for variables selected by the analyst. This is referred to as the “line up” process, and helps to promote consistency in our baseline forecasts from month to month, minimizing confusion over the outlook. An initial “lined up” forecast is produced, which represents what the previous month’s forecast would have been if the analyst had knowledge of the next month’s external events.

» Values for exogenous model drivers are then updated, and a new model solved.

» This initial update to the baseline forecast is then handed to the country analysts, who evaluate the baseline changes and apply their expert judgment to make additional changes to the forecasts to reflect recent news, policy announcements and qualitative information beyond the data available for input to the model.

» After the country analysts make their initial assessment and adjustments, a team of regional experts assesses the forecasts and checks for cross-country consistency. When issues are found, they are discussed with the country analysts and resolved collaboratively, with the analysts making appropriate final adjustments prior to publication.

Updated baseline forecasts are typically published mid-month, and are followed one week later with updated forecasts for 11 standard alternative macroeconomic scenarios for each country (see Table 2).

Each scenario begins as an exact copy of the baseline forecast, generated by a combination of pre-configured scenarios, as determined by other models. The appropriate variables to shock and the shock size are set to specified values to replicate the targeted severity.

Table 2: Moody’s Analytics Standard Global Scenarios

<table>
<thead>
<tr>
<th>Scenario Code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>S0</td>
<td>Extreme Upside (96th percentile demand shock)</td>
</tr>
<tr>
<td>S1</td>
<td>Stronger Near-Term Growth (90th percentile demand shock)</td>
</tr>
<tr>
<td>S2</td>
<td>Monetary Growth (75th percentile demand shock)</td>
</tr>
<tr>
<td>S3</td>
<td>Moderate Growth (50th percentile demand shock)</td>
</tr>
<tr>
<td>S4</td>
<td>Promoted Slump (5th percentile demand shock)</td>
</tr>
<tr>
<td>S5</td>
<td>Below-Trend Recession (10th percentile demand shock)</td>
</tr>
<tr>
<td>S6</td>
<td>Severe Recession (4th percentile demand shock)</td>
</tr>
<tr>
<td>S7</td>
<td>Next Cycle Recession</td>
</tr>
<tr>
<td>S8</td>
<td>Low Oil Price</td>
</tr>
<tr>
<td>S9</td>
<td>Commodity Sensitivity Scenario</td>
</tr>
<tr>
<td>S10</td>
<td>Sovereign Stress Scenario</td>
</tr>
<tr>
<td>S11</td>
<td>Moderate Stress Scenario</td>
</tr>
</tbody>
</table>

In some cases, just the first of these changes to the value of exogenous global inputs—is sufficient to produce a large shock response. In most cases, however, the impact is measurable but not significant. A recession in the U.S., for instance, may trigger a recession in Canada but it would not be enough on its own to push China, Brazil or South Africa into recession. As a result, severe up, and downside scenarios in these countries typically rely on assumptions that alter the values of domestic, endogenous variables.

The use of dummy variables for recession and financial crisis allow a single, transparent lever to be pulled that produces shocks to consumption, investment, wage growth and financial markets that are consistent with each other and with historical experience. However, binary variables do not easily allow for proper severity calibration to target probabilities. To achieve the desired severity in output, unemployment, inflation and other variables, endogenous variables are turned in exogenous assumptions, which then drive the rest of the model. Responsibility lies with the country experts for selecting the appropriate variables to shock and the degree to which they need to be adjusted, consistent with a written scenario narrative and a calculated severity/probability curve for that country.

The first set of Moody’s Analytics standard scenarios reflect demand shocks of various intensity. The specific nature of the demand shock varies with evolution in specific risk profile of each country, but the severity is calibrated to country-specific probability distributions calculated based on historical experience. The Moody’s Analytics baseline reflects our projection of the median, or 50th percentile scenario, meaning that our assessment there is an equal probability that the economy might perform better or worse than the baseline forecast. By contrast, the S1 upside scenario projects faster growth and lower unemployment to a degree to which in our judgment the economy has a 1-in-10 chance of performing any better. Similarly, our most severe downside scenario, S4, is calibrated to a reflect a downturn of a severity that would be expected with no more than a 4% probability.

These probability-calibrated scenarios are generated through a collection of shocks that adhere to a strict narrative of assumptions deemed “most likely” to produce the desired outcomes. Assumptions about shocks are calibrated to ensure they are sufficient to replicate the targeted severity.
In addition, Moody’s Analytics produces several standard scenarios (S5 on S9), in which specific alternative assumptions are targeted, as opposed to choosing assumptions to target outcome severities or probabilities. S9 is an extreme recession scenario set to achieve a specific severity, which presents an alternative to S4, which has a constant probability but thus varying severity as current economic conditions change over time. The custom "CF" forecast provides an alternative to the baseline forecast, targeting the consensus outlook across a range of third-party published forecasts.

The standard scenarios provide a wholesale solution to many clients’ needs, including internal risk assessment, regulatory stress-testing, and expected loss calculations including internal risk assessment, regulatory forecasts. These standard scenarios can also extend these standard projections in a variety of ways to reflect changed assumptions about the nature of global markets, with top-down pass-through effects to all countries simultaneously. In the second example, a forecast assumption within one specific country can be altered with direct implications for the forecast in that country and indirect spill-over effects to other countries via trade or financial linkages. Examples might include a hike in the European Central Bank's policy rate, or a devaluation of the Hong Kong dollar. In the third example, a variable typically thought of as endogenous—determined by the model solution—can be made exogenous and set to an explicit target value. This last approach is frequently employed in regulatory stress-testing, where financial institutions are required to assess their performance under an explicit set of targets for variables such as GDP, unemployment, interest rates, stock prices and house prices.

Data sources and methods

All macro forecasting is done at a quarterly frequency. Interest rates, stock prices and other higher frequency data are converted to quarterly frequency using the appropriate technique for the series, such as averaging, summing, or taking end-of-period values. Data available only at an annual frequency, such as demographic projections from the World Bank, are converted to a higher quarterly frequency using a cubic spline interpolation method.

The historical data series forecasts in the model are sourced directly from national statistical offices wherever possible, to ensure that the forecasts reflect the most accurate and timely information available. Data from third party aggregators such as the World Bank, OECD and International Monetary Fund are used to supplement these primary sources under one or more of the following conditions:

- The data are available only from a multinational source.
- Data from primary sources under one or more of the following conditions:

- We do not possess use rights for a national source of the data.
- We use a definition differing from national definitions.
- The multinational source provides higher quality.
- Often, to maximize the quality, methodological consistency and cross-country comparability of forecasts, historical data are sourced from proprietary estimated series.

To improve the quality and comparability of the data across countries, reported historical data are also sometimes transformed in one or more of the following ways:

- Seasonal adjustment: When the primary source data are not reported seasonally adjusted, we use the U.S. Census Bureau X-13 program to produce seasonally adjusted data.
- Backcasting: For index data and retail sales, we extend the time series by using the growth rates of discontinued predecessor series. For example, we extend the base 2015 real retail sales data using growth rates from previous base year data.
- Homogenization: We rescale an international data series to facilitate cross-country comparison. Data valued in different concepts are annualized by multiplying quarterly values by four as needed.

Model evaluation and governance procedures

The Moody’s Analytics forecast models are continually evaluated by clients, country experts and other internal model users, an independent Model Validation team and perhaps most frequently through the ongoing quality control processes undertaken each month by the Model Development team charged with building and maintaining the models.
Changes necessary to specify equations when coefficients change the dynamic properties of the model after re-estimation. In particular, we have quality control procedures in place to flag any coefficient changes that alter the sign (very rare) of a coefficient, or those that cross zero (more common) the roots in a differential equation from stable to explosive.

Changes necessary to improve shock properties (in scenario testing) to better calibrate simulation responses to historical variations.

Changes necessary to improve the robustness (for example, to reduce the possibility of a model crash) of the simultaneous core, which may stretch with solution time and the possibility of non-convergence.

Changes necessary to reduce the possibility of a model crash (for example, a variable that cannot take on non-negative values falling below zero during a stress, or in response to adjustment of another model series).

Changes necessary to increase cross-country consistency, or within-country consistency (for example, the response of domestic prices to exchange rate shocks, or to foreign inflation trends).

In the six months or so following the construction of a new model there is often a "tuning" process on which model equations are changed frequently in an effort to deliver maximum performance. The acid test for any forecast model is always its ability to predict accurately out of sample. A model's ability to match in-sample data is important but only proves the ability of the model to predict the past, not the future. Any true out-of-sample testing for forecast accuracy must occur as a "live fire" exercise.

4 Creating and testing equations is a highly iterative process. However, we aim to proceed with an initial set of our base cases in a timely manner. For example, allowing using data update 2009 to prepare forecasts for 2010-2011 against available historical data which impacts, to a large extent, the forecast performance. Similarly, there are cross-calibration amounts to a good test, but the wrong model.

More important, the primary consideration in assessing model performance is always whether it performs the functions it was designed for. In the case of models built primarily to simulate the path of macroeconomic variables under alternative scenarios for regulatory stress testing and accounting purposes, it is not just forecast accuracy that is important but also the ability of the model to produce appropriate shock responses in an efficient and transparent manner.

As discussed previously, model evaluation is not easily done simply through inspection of each individual model equation or standard "model diagnostics" criteria such as information criteria, but solely on an individual basis, or problematic using standard econometric diagnostic tools for a combination of equations evaluated solely on an individual basis. Instead, diagnostic tools for a combination of equations are essential.

However, after the development of model testing and documentation is complete, the specifications of the equations are finalized and typically do not require re-estimation except in specific instances. This is because a well-built model should be stable, representing a large informal share of the economy, and volatile or highly inflationary macroeconomic conditions complicated byOkun's law relationship used to map changes in aggregate demand to employment and wage/price pressures. This may be either because the unemployment rate varies little, despite large swings in real GDP, or the fact that the unemployment rate varies greatly, but in a way uncorrelated with changes in real GDP. Such issues are typically flagged, and a diagnostic tool will be assigned a "low priority" indicating that no superior alternative solution or analysis is available immediately.

In some smaller, lower-income countries, data constraints, mis-measurement of concepts arising from a large informal share of the economy, and volatile or highly inflationary macroeconomic conditions complicate greatly the construction of a completely flexible, accurate model that forecasts well on its own without add factors. Ultimately, a set of equations can only help to project out the empirical patterns in the data that we have observed in the past. In these developing and often politically, socially, or economically unstable countries, past performance is not always the best guide to future conditions. Models for such countries must be tested and validated in an environment that is as much like the one in which the model is expected to perform on its own. In these countries, the Model Development team inspects the output of these tests to check for potential issues, and re-estimates as necessary if problems are found.

In many cases, most commonly in emerging markets, problems are identified, but then even after careful research and testing no obvious solution is found. A common example is in countries where the reported unemployment rate bears little or no relationship to activity in the goods market, violating the standard Okun's law relationship used to map changes in aggregate demand to employment and wage/price pressures. This may be either because the unemployment rate varies little, despite large swings in real GDP, or the fact that the unemployment rate varies greatly, but in a way uncorrelated with changes in real GDP. Such issues are typically flagged, and a diagnostic tool will be assigned a "low priority" indicating that no superior alternative solution or analysis is available immediately.

In some smaller, lower-income countries, data constraints, mis-measurement of concepts arising from a large informal share of the economy, and volatile or highly inflationary macroeconomic conditions complicate greatly the construction of a completely flexible, accurate model that forecasts well on its own without add factors. Ultimately, a set of equations can only help to project out the empirical patterns in the data that we have observed in the past. In these developing and often politically, socially, or economically unstable countries, past performance is not always the best guide to future conditions. Models for such countries must be tested and validated in an environment that is as much like the one in which the model is expected to perform on its own.
and concept coverage. In the meantime, the forecast models serve as valuable tools to assist analysts in the calculation of consistent and statistically justifiable baseline and scenario forecasts.

- Wages (FYPEWS) and personal disposable income (FYPD). Wages are modeled as an equilibrium condition between a wage bargaining curve among workers supplying labor and firms’ labor demand curve. Workers are assumed to bargain over their expected average real wages based on trend productivity growth, with bargaining power affected by the unemployment rate.

- Monetary policy rate (FRMP). The short end of the yield curve is anchored by central bank policy, which in flexible exchange rate countries is set in accordance with a Taylor rule, which predicts target rate set by the central bank to minimize deviations in inflation and the output gap from desired levels. A zero-lower bound is assumed, such that the central bank sets interest rates at a minimum of 0.1% when economic conditions imply an optimal target rate below zero. Although endogenously determined by the model, the policy rate forecast is usually treated as an exogenous assumption, determined by the analyst through add factors to account for non-quantitative information such as a policy bias or advance guidance on rate hikes that is telegraphed to markets by the central bank.

- 10-year government bond yield (FRGTY10Y). Longer-maturity interest rates are anchored by a forecast for the 10-year bond rate, in contrast to the policy rate, which is largely assumed to respond to domestic conditions, with arbitrage in global debt and currency markets typically leading to bond yields in most advanced countries moving in near-lock step. For this reason, bond yields are often measured as spreads over a risk-free rate, proxied by the German bund in the euro zone and U.S. Treasury yields in the rest of the world. The spreads can vary with cur rency and financial market volatility, domestic monetary policy, and the level of government debt as a share of GDP.

- Exchange rates (FTFXIUSA). Countries are assumed to have either a fixed or a floating exchange rate regime. In the former case, the bilateral nominal exchange rate is forecast as a random walk, and the real effective exchange rate (FTFXTW$) is then determined by an identity relating the REER to the nominal bilateral rate and the ratio of domestic to foreign prices. In the case of floating rates, a target REER (FTFXTW$) is forecast as a stationary process in which mean-reversion is driven by a long-run purchasing power parity condition, and short-run deviations occur in response to changes in interest rates, market uncertainty/volatility, and expected growth.

- Consumer price index (FCPI). All inflation rates are tied to the forecast for consumer price inflation, which is specified using a firm price-setting equation that draws on recent macroeconomic theory. Increases in prices are assumed to depend on the firms’ known costs—as proxied by energy prices, the cost of imported inputs, and labor costs—and the rate of expected inflation, which represents firms’ forecast of the prices they will face from their competitors’ and suppliers’ prices, once their own prices have been set. The output gap, or some other measure of slack, is usually included as well to account for changes in firms’ pricing power, which affect their profit mark-ups and discounting behavior.
Appendix 1: “Template” equation specifications for initial model estimation for each country

- Unemployment rate (model mnemonic FLBR): The unemployment rate forecast using Okun’s law, a relatively tight empirical correlation seen in most advanced countries between the level of unemployment and deviations in real GDP from its trend. This specification varies across countries only with respect to the transformation used (levels, differences or a combination of the two) and lag lengths in GDP growth.

- Employment (FLBE) and labor force (FLBF) growth: Employment is cast as an identity, given unemployment, and the size of the labor force. The labor force is forecast as a mean reverting AR(1) process relative to the potential labor force, which is determined by trend participation rate and growth in the working-age population. In the near-term, labor force participation responds to cyclical shocks in the unemployment rate but converges to a constant long-run path set by exogenous assumptions.

- Private consumption (FC$): Consumption is forecast in per-capita terms as a Keynesian-style consumption function of expected income and target savings augmented with wealth effects. The target savings rate depends on interest rates and usually some measure of financial conditions. Expected income is proxies by current income and a forecast of the expected growth rate, an endogenous variable.

- Public consumption (FG$). Government current spending in the model is assumed to follow a naïve trend, in accordance with the budgeting process. Government expenditures and tax rates are assumed to be largely exogenous, with values overidden by the model user to match publicly available budget plans. However, the public spending equation usually includes an endogenous fiscal constraint: whereby an increase in the level of the debt as a share of the economy slows the growth in future spending. This improves long-run model stability and helps to simulate the economic impacts of politically induced austerity that follow severe downturns.

- Fixed capital formation (FIF$). Investment spending functions differ more significantly from country to country than most equations. This is because the drivers of investment are often different depending on factors such as the composition of domestic firms, the depth and maturity of domestic capital markets as well as the stability of capital markets, differential are of utility and risk aversion, and the structure of corporate and institutional investors. However, investment is more of a function primarily of expected future demand, pricing, interest rates, and growth in the book value of assets. In most countries, a real interest rate is used as a proxy for the cost of capital. In large net export countries, oil prices are used as a proxy for a commodity price, with smaller net exporting countries, real prices are associated with a drag on investment.

- Exports (FEX$) and imports (FIM$). Real exports and imports are modeled as a function of price and income using standard demand theory. In this case, price is represented by the country’s estimated real effective exchange rate (FEXFWS I), and income is represented by a proxy for foreign GDP in the case of exports, and domestic demand in the case of imports. To ensure consistency of the resulting nominal trade balance with changes in global saving and investment trends, and to allow a lever for adjustment, an error-correction term is included to ensure that the real trade balance evolves to align the current account balance with an adjustable target (FT-ABGD_T_IGEO).

- Wages (FYFEWS) and personal disposable income (FYFP). Wages are modeled as an equilibrium condition among workers supplying labor and firms labor demand curve. Wages are assumed to bargain over their expected average real wages based on trend productivity growth, with bargaining power affected by the unemployment rate.

- Monetary policy rate (FRMP). The short end of the yield curve is anchored by central bank policy, which in flexible exchange rate countries is an in accordance with a Taylor rule, which predicts a target rate set by the central bank to minimize deviations in inflation and the output gap from target levels. A zero lower bound is assumed, such that the central bank sets the interest rates at a minimum of 0.1% when economic conditions imply an optimal target rate below zero. Although endogenously determined by the model, the policy rate forecast is usually treated as an exogenous assumption, determined by the analyst through the addition of factors to account for non-quantitative information, such as a policy bias or advance guidance on rate hikes that is telegraphed to markets by the central bank.

- 10-year government bond yield (FRG10Y). Longer-maturity interest rates are anchored by forecasts for the 10-year bond rate. In contrast to the short end of the yield curve, which is largely assumed to respond to domestic conditions, arbitrage in global debt and currency markets typically leads to bond yields in most advanced countries moving in near-lock step. For this reason, bond yields are often measured as spreads over a risk-free rate, proxied by the German bund in the euro zone, and...
U.S. Treasury yields in the rest of the world. Risk spreads can vary with currency and financial market volatility, domestic monetary policy, and the level of government debt as a share of GDP.

» Exchange rates (FTFXIUSA). Countries are assumed to have either a fixed or a floating exchange rate regime. In the former case, the bilateral nominal exchange rate relative to the U.S. dollar (FTFXIUSA) is forecast as a random walk. The real effective exchange rate (FTFXTW$) is then determined by an identity relating the REER to the nominal bilateral rate and the ratio of domestic to foreign prices. In the case of floating rates, a target REER (FTFXTW$$_I$$) is forecast as a stationary process in which mean-reversion is driven by a long-run purchasing power parity condition, and short-run deviations occur in response to changes in interest rates, market uncertainty/volatility, and expected growth.

» Consumer price index (FCPI). All inflation rates are tied to the forecast for consumer price inflation, which is specified using a firm price-setting equation that draws on recent macroeconomic theory. Increases in prices are assumed to depend on changes in the firms’ known costs—as proxied by energy prices, the cost of imported inputs, and labor costs—and the rate of expected inflation, which represents firms’ forecast of the prices they will face from their competitors’ and suppliers and their own prices have been set. The output gap, or some other measure of slack, is usually included as well to account for changes in firms’ pricing power, which affect their profit margins and discounting behavior.
Appendix 2: Examples of top-down/bottom-up equation specifications

» A coincident economic indicator (FCEI_IEUZN) is used as a proxy for euro zone GDP. This is determined by predictors of euro zone growth, and then in turn feeds expenditure components throughout the euro zone. These components sum to equal each euro zone country’s real GDP forecast, which can be summed to compute the aggregate real GDP (FGDPS_IEUZN). In this way, FCEI_IEUZN is used as a “lever” to generate a forecast (FGDPS_IEUZN), but within a recursive (not simultaneous) framework that increases model stability, tractability and solution speed.

» A series for core euro zone inflation (FCPIHXAQ_IEUZN) is similarly used as a driver for individual euro zone country inflation rates. These inflation rates ultimately go into the calculation of an aggregate for euro zone inflation (FCPIH_IEUZN).

» An intermediate (designated by “I”) series (FTFXTW$_I$) reflects a country’s predicted real effective exchange rate (REER). In floating rate countries, this represents the primitive for exchange rate forecasts. It is a mean-reverting forecast that varies with interest rates, expectations, commodity prices, real exchange rates and CPI forecasts, among others.

The U.S., euro zone and China are the three largest drivers of the global economy, and as such they also serve as points of entry in tuning the overall global forecast. In particular, there are a number of top-down model drivers that play an outsize role in determining growth, inflation, stock prices, exchange rates, interest rates and credit spreads in the rest of the economy. The main “tuning levers” for the U.S. are:

« FGDP$_US$—Real GDP.
« FCPIU$_US$—Consumer price index.
« FPDIGDP$_US$—GDP implicit price deflator.
« FTWDBRD$_US$—Real weighted average exchange value of U.S. dollar: Broad index (this drives REER which then feeds back to the REER FTFXTW$_I$ USA).
« FCPWTI$_US$—West Texas Intermediate price of crude oil (this drives Brent oil, which forms the price of the series FPCPOIL$Q.IWRLD, or real global oil prices).
« FRTB3M$_US$—3-month Treasury bill rate, used as part of the TED spread.
« FRGT5Y$_US$—5-year Treasury bond, which determines the short end of the yield curve.
« FRGT10Y$_US$—10-year Treasury bond, which determines the long end of the yield curve.
« RAILBOM$_US$—LIBOR, which is used as a spread vs. FRG0T3M$_US$.
« FRBAAC$_US$—Moody’s Baa corporate bond yield, used as a level and as a spread vs. FRGT10Y$_US$.

In addition, for Europe the main tuning levers are:

« FRMP_IEUZN—The European Central Bank policy rate.
« FTFXIUSAQ_IEUZN—Euro exchange rate with the U.S. dollar.
« FCEI_IEUZN—Conference Board’s Coincident Indicator.
« FCPIMHAQ_IEUZN—Core euro zone inflation.

In Asia, real GDP for China and Japan are the primary levers that determine export demand, commodity prices and growth expectations across much of Asia and Latin America.
About the Author

Mark Hopkins is a director at Moody’s Analytics, with responsibilities for international macroeconomic research and global forecasting, including the design and maintenance of the Moody’s Analytics suite of country forecast models. Dr. Hopkins has also been responsible for forecasting Canada’s economy and U.S. federal fiscal policy. Previously, he taught macroeconomics at Gettysburg College and served as international economist on the staff of the President’s Council of Economic Advisers. He has published in the areas of international economics, economic growth, and foreign policy. He received his PhD in economics from the University of Wisconsin-Madison, an MSc from the London School of Economics, and a BA from Wesleyan University.
About Moody's Analytics

Moody's Analytics provides financial intelligence and analytical tools supporting our clients' growth, efficiency and risk management objectives. The combination of our unparalleled expertise in risk, expansive information resources, and innovative application of technology helps today's business leaders confidently navigate an evolving marketplace. We are recognized for our industry-leading solutions, comprising research, data, software and professional services, assembled to deliver a seamless customer experience. Thousands of organizations worldwide have made us their trusted partner because of our uncompromising commitment to quality, client service, and integrity.

Concise and timely economic research by Moody's Analytics supports firms and policymakers in strategic planning, product and sales forecasting, credit risk and sensitivity management, and investment research. Our economic research publications provide in-depth analysis of the global economy, including the U.S. and all of its state and metropolitan areas, all European countries and their subnational areas, Asia, and the Americas. We track and forecast economic growth and cover specialized topics such as labor markets, housing, consumer spending and credit, output and income, mortgage activity, demographics, central bank behavior, and prices. We also provide real-time monitoring of macroeconomic indicators and analysis on timely topics such as monetary policy and sovereign risk. Our clients include multinational corporations, governments at all levels, central banks, financial regulators, retailers, mutual funds, financial institutions, utilities, residential and commercial real estate firms, insurance companies, and professional investors.

Moody's Analytics added the economic forecasting firm Economy.com to its portfolio in 2005. This unit is based in West Chester PA, a suburb of Philadelphia, with offices in London, Prague and Sydney. More information is available at www.economy.com.

Moody's Analytics is a subsidiary of Moody's Corporation (NYSE: MCO). Further information is available at www.moodysanalytics.com.

DISCLAIMER: Moody's Analytics, a unit of Moody's Corporation, provides economic analysis, credit risk data and insight, as well as risk management solutions. Research authored by Moody's Analytics does not reflect the opinions of Moody's Investors Service, the credit rating agency. To avoid confusion, please use the full company name "Moody's Analytics", when citing views from Moody's Analytics.

About Moody's Corporation

Moody's Analytics is a subsidiary of Moody's Corporation (NYSE: MCO). MCO reported revenue of $4.8 billion in 2019, employs more than 11,000 people worldwide and maintains a presence in more than 40 countries. Further information about Moody's Analytics is available at www.moodysanalytics.com.
MOODY’S CREDIT RATINGS AND MOODY’S PUBLICATIONS ARE NOT INTENDED FOR USE BY RETAIL INVESTORS AND IT WOULD BE RECKLESS AND INAPPROPRIATE FOR RETAIL INVESTORS TO USE MOODY’S CREDIT RATINGS OR MOODY’S PUBLICATIONS WHEN MAKING AN INVESTMENT DECISION. IF IN DOUBT YOU SHOULD CONTACT YOUR FINANCIAL OR OTHER PROFESSIONAL ADVISER.

ALL INFORMATION CONTAINED HEREIN IS PROTECTED BY LAW, INCLUDING BUT NOT LIMITED TO, COPYRIGHT LAW, AND NONE OF SUCH INFORMATION MAY BE COPIED OR OTHERWISE REPRODUCED, REPACKAGED, FURTHER TRANSMITTED, TRANSFERRED, DISSEMEDIATEKED, DISTRIBUTED OR RESOLD, OR STORED FOR SUBSEQUENT USE FOR ANY SUCH PURPOSE, IN WHOLE OR IN PART, IN ANY FORM OR MANNER OR BY ANY MEANS WHATSOEVER, BY ANY PERSON WITHOUT MOODY’S PRIOR WRITTEN CONSENT.

All information contained herein is obtained by MOODY’S from sources believed by it to be accurate and reliable. Because of the possibility of human or mechanical error as well as other factors, however, all information contained herein is provided “AS IS” without warranty of any kind. MOODY’S adopts all necessary measures so that the information it uses in assigning a credit rating is of sufficient quality and from sources MOODY’S considers to be reliable including, when appropriate, independent third-party sources. However, MOODY’S is not an auditor and cannot in every instance independently verify or validate information received in the rating process or in preparing the Moody’s publications.

To the extent permitted by law, MOODY’S and its directors, officers, employees, agents, representatives, licensors and suppliers disclaim liability to any person or entity for any indirect, special, consequential, or incidental losses or damages whatsoever arising from or in connection with the information contained herein or the use of or inability to use any such information, even if MOODY’S or any of its directors, officers, employees, agents, representatives, licensors or suppliers is advised in advance of the possibility of such losses or damages, including but not limited to: (a) any loss of present or prospective profits or (b) any loss or damage arising where the relevant financial instrument is not the subject of a particular credit rating assigned by MOODY’S.

To the extent permitted by law, MOODY’S and its directors, officers, employees, agents, representatives, licensors and suppliers disclaim liability for any direct or compensatory losses or damages caused to any person or entity, including, but not limited to by any negligence (but excluding fraud, willful misconduct or any other type of liability that, for the avoidance of doubt, by law cannot be excluded) on the part of, or any contingency within or beyond the control of, MOODY’S or any of its directors, officers, employees, agents, representatives, licensors or suppliers, arising from or in connection with the information contained herein or the use of or inability to use any such information.

NO WARRANTY, EXPRESS OR IMPLIED, AS TO THE ACCURACY, TIMELINESS, COMPLETENESS, MERCHANTABILITY OR FITNESS FOR ANY PARTICULAR PURPOSE OF ANY SUCH RATING OR OTHER INFORMATION OR INFORMATION IS GIVEN OR MADE BY MOODY’S IN ANY FORM OR MANNER WHATSOEVER.

Moody’s Investors Service, Inc., a wholly-owned credit rating agency subsidiary of Moody’s Corporation (“MCO”), hereby discloses that most issuers of debt securities (including corporate and municipal bonds, debentures, notes and commercial paper) and preferred stock rated by Moody’s Investors Service, Inc. have, prior to assignment of any rating, agreed to pay to Moody’s Investors Service, Inc. for appraisal and rating services rendered by it fees ranging from $1,000 to approximately $2,700,000. MCO and MIS also maintain policies and procedures to address the independence of MIS’s ratings and rating processes. Information regarding certain affiliations that may exist between directors of MCO and rated entities, and between entities who hold ratings from MIS and have also publicly reported to the SEC an ownership interest in MCO of more than 5%, is posted annually at www.moodys.com under the heading “Investor Relations — Corporate Governance — Director and Shareholder Affiliation Policy.”

Additional terms for Australia only: Any publication into Australia of this document is pursuant to the Australian Financial Services License of MOODY’S. Moody’s Investors Service Pty Limited ABN 61 003 399 657AFSL 336969 and/or Moody’s Analytics Australia Pty Ltd ABN 94 105 136 972 AFSL 383569 (as applicable). This document is intended to be provided only to “wholesale clients” within the meaning of section 761G of the Corporations Act 2001. By continuing to access this document from within Australia, you represent to MOODY’S that you are, or are accessing the document as a representative of, a “wholesale client” and that neither you nor the entity you represent will directly or indirectly disseminate this document or its contents to “retail clients” within the meaning of section 761G of the Corporations Act 2001. MOODY’S credit rating is an opinion as to the creditworthiness of a debt obligation of the issuer, not on the equity securities of the issuer or any form of security that is available to retail investors. It would be reckless and inappropriate for retail investors to use MOODY’S credit ratings or publications when making an investment decision. If in doubt you should contact your financial or other professional adviser.

Additional terms for Japan only: Moody’s Japan K.K. (“MJKK”) is a wholly-owned credit rating agency subsidiary of Moody’s Group Japan G.K., which is wholly-owned by Moody’s Overseas Holdings Inc., a wholly-owned subsidiary of MCO. Moody’s SF Japan K.K. (“MSFJ”) is a wholly-owned credit rating agency subsidiary of MJKK. SFJ is not a Nationally Recognized Statistical Rating Organization (“NRSRO”). Therefore, credit ratings assigned by MJKK and MSFJ are Non-NRSRO Credit Ratings. Non-NRSRO Credit Ratings are assigned by an entity that is not a NRSRO and, consequently, the rated obligation will not qualify for certain types of treatment under U.S. laws. MJKK and MSFJ are credit rating agencies registered with the Japan Financial Services Agency and their registration numbers are FSA Commissioner (Ratings) No. 2 and 3 respectively.

MJKK or MSFJ (as applicable) hereby disclose that most issuers of debt securities (including corporate and municipal bonds, debentures, notes and commercial paper) and preferred stock rated by MJKK or MSFJ (as applicable) have, prior to assignment of any rating, agreed to pay to MJKK or MSFJ (as applicable) for appraisal and rating services rendered by it fees ranging from JPY125,000 to approximately JPY250,000,000.

MJKK and MSFJ also maintain policies and procedures to address Japanese regulatory requirements.