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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.

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BY MARK HOPKINS

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Chart 1: Global Forecast Coverage

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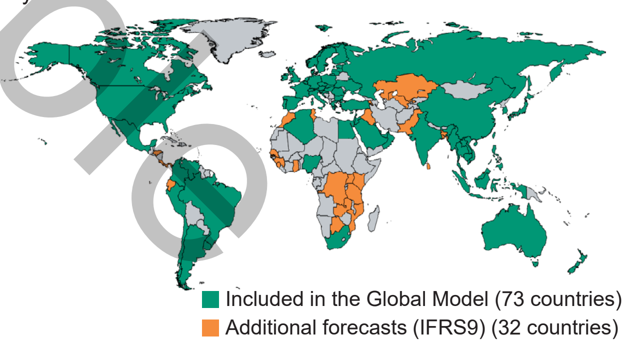


Sources: Moody's Analytics

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.

- P**redictive 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."

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

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

Source: Moody's Analytics

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).

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).

$$Y_t = aY_{t-1} + bX_t + cZ_t + \varepsilon \qquad \backslash s$$
$$X_t = \rho_X X_{t-1} + dY_{t-1} \qquad \backslash s$$
$$Z_t = \rho_Z Z_{t-1} - fY_{t-1} \qquad \backslash s$$

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:

ρ_X	Small (close to 0)
ρ_Z	Big (close to 1)
$b*d$	Big
$c*f$	Small

In this case, a positive shock to GDP (ε) 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-

ed by both theory and the data, lies the traditional approach of building and estimating structural models of the macroeconomy employed by most professional macroeconomic forecasters, including Moody's Analytics.

A common example of the time-series approach to forecasting is the vector autoregression 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 assumptions are necessary only when seeking to infer causal effects from shocks, not for prediction.

The advantage of this approach is that by dispensing with the need for economic theory and relying instead on observable historical covariation, VARs are largely immune from criticism 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 to predict the dynamic responses of variables, or "impulse responses" under alternative scenarios. However, the VAR method suffers from at least three important limitations.

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).

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 these models, equations are derived from equilibrium expressions for the aggregate outcomes resulting from 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 with a DSGE. Deriving tractable model solutions also requires strong assumptions (for example, all consumers and firms are identical with specific, simple preferences and production technologies). As a result, DSGEs remain most popular within academic circles, where the value of the model predictions is often of less interest than the elegance of the model's design.

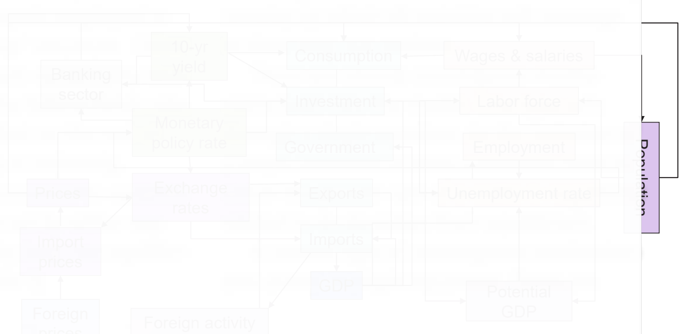
The third approach offers a versatile and powerful alternative. Despite their great value in specific contexts, the limitations of VARs and DSGEs—particularly in terms of scalability—led to the continued use of structural macroeconometric models by most private and government forecasters for more than a half century. These models are built upon familiar textbook macroeconomic theory: roughly, the IS/LM model of aggregate demand and a Phillips curve relationship determining aggregate supply. These textbook equations are made operational as forecasting tools through the use of econometric estimation to find the right "fit" of the theoretical relationship in the observed data (see Chart 2).

By taking a middle ground between theory and data, this approach attains neither the theoretical elegance of the DSGE approach nor the empirical flexibility of a VAR. Nevertheless, it manages to avoid their main shortcomings. In the structural approach used by Moody's Analytics, economic theory puts restrictions on econometric specifications in ways that allow for more efficient estimation and better long-run forecast performance than a VAR 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 constrain their explanatory scope.

The greatest advantage of the structural approach, however, is scalability. While VARs and DSGEs can incorporate no more than a few variables of interest, such as aggregate GDP, a benchmark bond yield, and CPI inflation, structural macroeconomic models generally include a rich array of macroeconomic data, providing great detail on the composition of both spending and industrial activity, the slope of the entire yield curve, and various prices for goods, services and assets throughout 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 in fact "structural" at all was challenged famously by Nobel laureate Robert Lucas, who argued that most economic relationships in the economy—even well-known, stable and 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

Chart 2: Structural Model Methodology



Source: Moody's Analytics

economy. 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 on correlations established with lagged 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 productivity growth, fiscal and monetary policy action, 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 closely on these broad macroeconomic aggregates. More often, bank solvency hinges on asset prices, credit quality, or industrial performance and employment in certain segments of the economy, such as the housing or commercial real estate market.

In such instances, where the goal is not to produce a forecast of GDP and inflation but to take these as inputs and extrapolate them out to a much broader set of economic indicators, both VARs and DSGEs are robbed of their primary value. At the same time, these stress-testing and scenario exercises capitalize on the primary strengths of traditional structural macroeconomic models, which are transparency and the ability to operate on a very large scale.

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 and dynamically stable as a system, and not just a random collection of equations that are justifiable on their own but nonsensical 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.

For example, consider a credit model in which a regression equation is fit to loan losses conditional on current and lagged unemployment and interest rates. A model user must simply input assumed future values for the unemployment and interest rates to generate a prediction for loan losses. If the model equation is judged to perform well, then there is no basis to assume losses would be anything other than predicted by the model. Any non-model information and qualitative judgments would likely be incorporated through changed assumptions on the exogenous model inputs, not adjustment of the endogenous model output. As a result, standard statistical testing and residual diagnostics are critical to ensure the validity of the conditional expectation relationship between loan losses and the covariates.

By contrast, consider a model where all three of these inputs—credit losses, interest rates and unemployment—are endogenous and depend on one another. In this situation, there are no exogenous inputs to be adjusted. Rather, the model user is forced to be an active participant in the forecast process—to manipulate the endogenous variables directly to incorporate alternative assumptions. The quality of the forecast for loan losses depends not just on the specification of one equation but of three, and more important than 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 (the higher the R-squared) 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 single equation time series forecasts or credit loss modeling. In particular, the role of a priori theory, consistency of causal ordering across equations, and the accuracy of 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 forecasting 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 stable, 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. Exports 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, proxied by the U.S. Treasury yield.

» **Price linkages.** Generally speaking, the inflation rate in economies with a fixed exchange rate are anchored by the growth rate of foreign prices. Inflation in countries with a floating exchange rate is anchored by inflationary expectations, but influenced by a number of global factors, including commodity prices (particularly oil prices), exchange rates, and the price of foreign goods.

» **The balance of payments.** Direct and portfolio investment flows are modeled as part of the financial account of the Balance of Payments. Direct investment flows in and out of the country are assumed to depend on investor expectations of growth and a country's competitiveness, defined by its real effective exchange rate. Portfolio capital flows are forecast on a net basis, with a specification motivated by the Balance of Payments identity that the current, capital and financial accounts must sum to zero. Although an identity, the capital account is not forecast but instead treated as a stochastic error term within the portfolio balance equation.

» **Investment linkages.** Foreign direct investment into an economy is one determinant of fixed capital formation, providing a second demand linkage beyond exports. In practice, this effect is much weaker than trade linkages.2 In addition, psychological linkages play an important role in investment. Expectations of future domestic GDP growth, which affect investor decision making in both the goods and financial markets, are influenced in part by global shocks, including those affecting the performance of the large engines of global growth: the U.S., euro zone, China, Japan and Brazil.

2 This is because of three reasons: (1) a usually small share of foreign funding of domestic investment, (2) the volatility of the FDI series, which reduces the correlation with fixed investment, and (3) measurement issues that affect the timing of the relationship of foreign capital flows and NIPA spending that also reduce the empirical correlation.

Equation specification

The Moody's Analytics global macro model is a structural model. This means each equation is specified not merely to maximize its predictive value, but also to abide by textbook macroeconomic theory. Wherever possible, theory is applied strictly, with the specific functional forms motivated as the first order solution to some optimization problem, and with the equation parameters having a clear structural interpretation. In other cases, theory is applied in a much broader sense, by employing first order Taylor rule expansions to generate log-linear regression specifications between dependent and independent variables, or specifying equations according to empirically validated rules of thumb, like Okun's law, or a professional consensus in the field, such as the so-called Taylor rule for central bank interest rate setting.

In each case, parameters are estimated econometrically based on the observable historical covariation over the equation's macroeconomic time series. Below are descriptions of important methodological considerations in specifying and estimating these equations:

» **Specification searches.** Typically, theoretical macroeconomic models describe either static relationships (for example, the textbook IS curve) or involve some type of dynamic relationship over a non-specific time period (for example, asset pricing equations). In either case, applying a theoretical relationship to the data and implementing it practically in a forecast setting typically requires some type of specification search. Theory places structure on the data, but the data are also used to discover empirical facts about relevant lag lengths and periodicity. These facts can differ across countries, as can data quality, volatility and economic significance. For example, stock market valuations may play a more important role in business investment decisions in some economies than others. Thus, for a given variable, the same specification is used initially for each country, but the final specification for that concept may vary across countries. This variation may be for empirical reasons—shocks propagate more slowly in some countries, requiring longer lag lengths. Or it may be for practical reasons—an explanatory variable may appear in one country where there is a long historical times series available, but be dropped from an equation where its inclusion would significantly reduce the sample size.

» **Equation parsimony.** In theory, everything in the world is endogenous. In practice, the global macro model was built to function as an effective tool for addressing a wide array of possible use. This requires maximum flexibility in terms of cross-variable linkages and associations, and directions of causality among variables. However, in a model with 10,000 equations and unknowns, some structure is required to ensure tractability and stability. For this reason, equations are generally specified in a way to include whatever variables are deemed most necessary, in whatever transformation of that variable makes it appear most significant, while excluding extraneous variables or those with low levels of statistical significance (high p-values). In general, though, theoretical and practical considerations always trump statistical ones. A variable that is theoretically relevant or represents an important linkage for ensuring proper shock propagation may be included in an equation even if it has a higher p-value (implied by a low t-statistic) than another, less theoretically important variable with a more significant p-value that is ultimately excluded for reasons of parsimony.

» **Linkage parsimony.** Just as parsimony in equations helps to alleviate problems of collinearity that can produce volatile and possibly inaccurate coefficient estimates, parsimony in the extent of cross-country linkages helps to reduce the size of the simultaneous model "core," which increases stability of the solutions and reduces iteration counts, and thus the required time to solve. Several approaches to linkage parsimony are taken:

» **Use of proxies vs. aggregates.** In theory, each country both determines and is influenced by world prices and interest rates. However, world prices and interest rates are not a primitive forecast with a stochastic equation. Rather, they are an aggregate that depends on the forecasts for all covered countries. For this reason, including just 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 superpower such as the euro zone, Japan or China as a proxy for the equivalent global aggregate concept. Ergo, 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 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"

Source: Moody's Analytics

to compute this solution, slowing the model solve speed and potentially creating instability should a shock be delivered into this simultaneous system of equations. To avoid such problems, we employ a number of "ex ante/ex post" concepts, in which a top-level variable representing some aggregate outcome is 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.

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-0.5*X) on Z. In performing econometric estimation of the parameters, there are always two main considerations:

» **The bias vs. variance trade-off.** Forecast error arises from bias and excessive variance in the forecast equations, which often can be linked to bias and excessive variance in the estimators used to generate equation coefficients. 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 method are done with a (subjective) view of what the modeler believes optimizes the results from the perspective of the bias-variance trade-off.

Examples include (but are not limited to): (1) introducing bias from omitted relevant variables versus increasing variance (and thus parameter instability from excessive multi-collinearity) by including extraneous variables, and (2) removing potential endogeneity bias through the 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 from a specification in levels to one in differences, or vice versa.

In instances where short history for one regressor leads to a severely truncated estimation sample, a proxy variable with longer history may be substituted, or the problem variable dropped altogether. In cases where coefficients seem significant and of the wrong sign, the residuals are inspected to account for possible omitted variable bias and corrective action is taken based on that analysis.

In general, traditionally reported regression statistics based on estimated residuals—such as the R2, coefficient t-tests, and the Durbin-Watson statistic—are treated as important diagnostics that provide information to the modeler but are not determinative of equation validity or appropriateness. The modeling bias is always toward the validity of the equation on theoretical grounds over econometric ones. This is because the primary purpose of the regression is not statistical inference. In the deterministic forecast solution, only the coefficient values matter, not the standard errors of those coefficients. Therefore, econometric "problems" like heteroskedasticity, serial correlation and non-normality of the error terms that produce inaccurate reporting of standard errors and associated p-values—but which do not preclude unbiased estimation of the coefficients—are considered secondary problems relative to those, like omitted variable bias and dynamic stability, that have implications for the actual forecast solution produced by the model equations.

To be clear, the statistical significance of coefficients, overall equation fit, and evidence of serial correlation in residuals are not entirely unimportant. These simply have different interpretations in the context of forecasting than they do in the more familiar "textbook treatment" of regression as a tool for statistical inference and hypothesis testing. For example:

- **t-statistics** traditionally are used in a test of the hypothesis that a covariate has zero impact on the dependent variable. This can be used to evaluate the significance of treatment effects or as part of a decision rule to include or exclude an auxiliary conditioning variable. In the context of a structural forecast model, theoretical considerations are primary in the decision to include or exclude a variable and the t-statistic is important largely for estimating 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 investment will respond much more strongly to a one-standard deviation shock to interest rates than it will to an analogous shock to stock prices.

- The R^2 of an equation measures 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 R2 is an important indicator of the degree to which the dependent variable will respond at all to shocks introduced in the model. This is important because for the model to work properly in scenario applications, shocks must be able to propagate through the model completely. If large shocks to GDP have little to no impact on the unemployment rate, then all other downstream variables that depend on employment rather than GDP, like income and many prices, may not respond appropriately to an exogenous shock to exports.

» The **Durbin-Watson test statistic** is useful for its standard role in revealing the presence of serial correlation in the residuals. In both standard backward-looking analytical and forward-looking forecasting applications this is important to know, as it suggests that 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 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.

» Non-stationarity of the variables in a time series regression, as commonly assessed by the Augmented Dickey-Fuller test, is an important consideration when conducting inference as the presence of a unit root renders reported standard errors invalid, along with any associated p-values for the coefficients. In the context of forecasting structural models, roots close to the unit circle are typically associated with a more practical concern: dynamic instability. Many of the model equations are modeled with a lagged dependent variable in level terms, which is intended to produce a mean-reversion effect that allows the model to simulate stable forecasts out to 30 years without values exploding to infinity or quantities falling secularly until they take on negative values, both of which can lead to a model crash. If a series is non-stationary, that mean-reversion disappears (in the case of a unit root) or reverses (if the root is greater than 1), causing the forecast to explode away from equilibrium rather than converging to it. For this reason, equations are purposefully modeled such that the dependent variable and covariates are all stationary. This typically requires some transformation of the variables, such as differencing the non-stationary series or modeling it as a stationary ratio of another non-stationary variable.

The following econometric and technical modeling considerations were also important in building the global model:

- **Equation stability.**
  - Equations modeled in levels with no lagged dependence will suffer "jump-off problems."
  - Equations modeled in changes (percent change or differences) may suffer from stability problems (need anchors, or ECM specification to ensure stability).
  - Equations modeled in four-quarter changes should be avoided—shocks propagate forward as undesired "cyclicality."
- **Causation vs. correlation.**
  - Lags or instrumental variables should be used where OLS estimates may be improperly estimated (that is, not reflect true casual relationships).
- **Short vs. long regressions.**
  - Equation specifications should trade off the following three desired criteria:
    - **Shockability.** Equations should have sufficient mechanisms built in to allow interesting and appropriate shock propagation, to generate scenarios.
    - **Parsimony.** Variables should be excluded that have a low signal/noise ratio (low t-statistics), to ensure stability and accuracy of forecasts.
    - In general, specifications for variables in the model core should err toward forecasts that are robust to perturbations to ensure model stability, while specifications for peripheral variables should maximize their response to shocks while remaining consistent with core drivers.

The use of event dummy variables

One type of dummy variable plays an important role in the global model: those "event" dummies indicating a discrete period-ic in conditions such as a recession, a financial crisis, or a cycle of hyperinflation. These variables are important in several respects.

First, they provide a natural lever with which to introduce the concept of an "exogenous shock." Most economic models operate by inputting values for exogenous variables and having the model return values for endogenous variables. In this case, one can construct alternative outputs simply by altering the exogenous inputs. In the global macroeconomic setting, however, there are few truly exogenous variables. GDP, income, prices, interest rates, exchange rates, trade balance, stock prices and house prices all depend on one another. Although one can produce a recession in a country by, for example, lowering consumption spending dramatically, to a large extent you have then simply assumed your conclusion. The goal of the dummy is to avoid exogenizing variables of interest that we want the model to tell us about. "Turning on" a country's recession dummy in a downside scenario avoids the need to overlay the model output with an assumption about consumption or investment spending, is more transparent in tracing back forecast output to inputs, and preserves the model's ability to transmit shocks by keeping key series endogenous.

Second, the use of recession and financial dummies in estimation help to reduce omitted variable bias. When estimating a structural relationship across time series, there are often structural breaks (temporary or permanent) where the relationship shifts in some way. A recession could trigger a sudden temporary increase in fiscal stimulus spending, a widening of credit spreads, a pullback on house purchases, or big-ticket durables spending. Not controlling for these factors may bias the coefficient estimates on included regressors, if the values of those regressors are correlated with the episodes of structural change. Evidence of such omitted effects can often be seen by examination of the residuals. The use of time dummies, a common option in econometric estimation, allows for structural breaks. Not accounting for this may conflate differing effects over time into a single coefficient. However, in the context of forecasting, a time dummy approach wastes information. The period 2007-2009 will never occur again. Yet, the relevant events of that period very well could recur. Creating an event dummy variable, such as DUM_RECESS, is econometrically equivalent to using a time dummy during the quarters of a recession, but it has an additional practical advantage; alternative forecasts for the event dummy can be set explicitly to motivate, in a transparent fashion, the construction of alternative scenarios in the forecast.

Third, dummies help capture the impacts of latent or non-quantifiable (that is, qualitative) factors such as investor psychology. Dummy variables are useful for quantifying the impact of an unknown latent factor that cannot be easily identified or measured. If the omitted variable bias in the regression was being generated simply by the existence of recessionary conditions, such as a high unemployment rate, then the optimal approach would not be to include that omitted variable directly. The problem with this arises when the variable under consideration (that is, the unemployment rate) does not have a clear structural relationship justifying its inclusion in the equation. In this case forecast problems can be introduced by changes in the proxy variable independent of changes in the "true" underlying latent factor inducing spurious changes in the forecast. For this reason, where the omitted variable is believed to be qualitative or non-observable, the dummy variable method is preferable to the proxy method. For example, the sudden emergence of fears of recession might spark a drop in equity prices. A recession is also associated with a rise in unemployment. However, the level of unemployment may not be structurally related to stock prices. In fact, higher unemployment may be generally associated with higher stock prices, out of a belief that the central bank will keep future interest rates lower than they otherwise might.

Fourth, the dummy variables help to generate more realistic dynamics. Another concern with using a proxy like the unemployment rate in a stock price equation would be the fact that the unemployment rate tends to rise and fall much more gradually than changes in equity prices. Using a recession dummy in an equity, investment or durables spending equation can help to produce a sudden, sharp movement in a forecast series in a downside scenario, matching the empirical dynamics commonly observed during recessions. By contrast, equations tied to variables that adjust gradually, or enter with some lag, produce much more slow-moving responses in which GDP, unemployment, inflation, equity prices and other variables drift away from the baseline in a recession scenario rather than sharply dropping away from it in a manner consistent with past experience for most countries.

Finally, incorporation of event dummies helps to reproduce empirically observable asymmetries. A final use of recession dummies is to help introduce asymmetries that are also evident in the data. An example would be Okun's law: a strong empirical (negative) correlation between the size of the output gap and the unemployment rate. Roughly speaking, across much of the OECD, the unemployment rate moves by about -0.4 times the percentage point difference in the growth rates of real GDP and its potential rate. This amounts to a trend line that fits the data quite well but also implies a symmetry between faster growth lowering the unemployment rate and slower growth raising it. On an incremental basis this symmetry does exist, but with more extreme swings we generally see unemployment rising sharply much more during the onset of recessions than we see it falling during boom periods. There is a natural floor on the unemployment rate but no equivalent ceiling, reflecting in part the fact that it is easier to engage in sudden, mass layoffs than sudden, mass hiring. Augmenting the Okun's relationship with a recession dummy helps to improve the equation fit by addressing this asymmetry in the data, and more accurately reproduce the shock properties and severities observed in the unemployment rate data during prior periods of stress.

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 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 that represents what the previous month's forecast would have been if the analyst had knowledge of the next months' data.

» Values for exogenous model drivers are then updated, and a new model solved to account for how these changes alter the domestic outlook.

» 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 the model equation and the baseline add-factors determined by the country expert. The model solutions are then shocked in three specified ways and resolved:

» Exogenous inputs such as foreign demand, commodity prices, global interest rates, and scenario values are evaluated, as determined by other models.

» Domestic exogenous variables, particularly dummy variables indicating the onset of recessionary conditions or financial shocks, are set to their scenario values.

» A set of specified endogenous variables, such as investment spending, policy rates and exchange rates, are set to specified values to further shock the model.

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 into exogenous assumptions, which then in turn 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 the risk profile of each country, but the severity of the shock is calibrated to country-specific probability distributions calculated based on historical experience. The Moody's Analytics baseline reflects our projection of the median, or "50%" scenario, meaning in 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.

Table 2: Moody's Analytics Standard Global Scenarios

S0	Extreme Upside (96th percentile demand shock)
S1	Stronger Near-Term Growth (90th percentile demand shock)
S2	Slower Near-Term Growth (25th percentile demand shock)
S3	Moderate Recession (10th percentile downside)
S4	Protracted Slump (4th percentile downside)
S5	Below-Trend Long-Term Growth (supply shock)
S6	Stagflation (supply shock)
S7	Next Cycle Recession
S8	Low Oil Price
S9	Constant Severity Downturn
CF	Consensus Forecast

Source: Moody's Analytics

In addition, Moody's Analytics produces several standard scenarios (S5 to S8) 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, a targeting the consensus outlook across a range of third-party published forecasts.

These standard scenarios provide a wholesale solution to many clients' needs, including internal risk assessment, regulatory stress-testing, and expected loss calculations under IFRS 9 or CECL accounting rules. Clients can also extend these standard global macroeconomic scenarios to allow for customized-idiosyncratic shocks. To generate a scenario, the model user begins with a current model solution (usually, but not necessarily the baseline forecast) and then resolves the model after altering one or more of the following types of series:

» Global market assumptions (such as commodity prices)
» National model assumptions (central bank policy rates, for instance)
» Endogenous forecast variables (Chinese imports, Canadian house prices, or Italian investment spending, as examples)

In the first case, the forecast path for a variable such as global oil prices is altered 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 spillover 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;
» We do not possess use rights for a nationally sourced series;
» For cross-country forecast consistency we use a definition differing from national definitions; or
» The multinational source data are of higher quality.
» Often, to maximize the quality, methodological consistency and cross-country comparability of forecasts, historical data are sourced from proprietary estimated series.3

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 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 and homogenize data to facilitate cross-country comparison. Data valued in currency are scaled to be in billions. Flow concepts are annualized by multiplying quarterly values by four as needed.

3 Standard examples include wages, disposable income and house prices, which are often reported on an inconsistent basis by national sources but often serve as the basis for cross-country comparisons. NIPA variables such as GDP are reported on a standardized, seasonally adjusted annualized basis, both in local currencies and in three comparable currencies: U.S. dollars, euros and PPP (purchasing power adjusted U.S. dollars).

Model evaluation and governance procedures

The Moody's Analytics forecast models are continually evaluated by clients, the 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.

Issues that have needed to be addressed during ongoing evaluations include:

» Changes necessary to respecify 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 (more commonly) 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 variation.

» Changes necessary to improve model stability (for example, to reduce the size of the simultaneous core, which reduces both solution time and the possibility of nonconvergence).

» 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 in 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]

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 in isolation. In the context of macroeconomic simultaneous equations model, standard "model selection" criteria such as information criteria do not always apply. This is because the forecast is not based on the performance of any one specific equation, but many equations interacting together. It is quite possible to have a model comprised of multiple equations that seem to pass muster individually, but which when combined produce inaccurate or highly unstable forecasts. Conversely, a useful, more accurate model can be constructed using a combination of equations that, evaluated solely on an individual basis, seem limited or problematic using standard econometric diagnostic tools for a single equation.

However, after the initial burn-in period of model testing and respecification 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 robust to new information, with estimated relationships that do not change significantly when additional data are introduced. The need for clear and up-to-date model documentation and validation results also discourages the frequent re-estimation of our models.

Nevertheless, the model is never completely static. Equation changes are often needed to react to rebasing or other changes to the underlying data series being forecast, by changing business needs or regulatory requirements, or simply by the introduction of new process efficiencies. Each month a list of issues requiring equation re-estimation or other model changes is compiled by the model development team. In the week prior to the next monthly baseline update, additional issues flagged by a preliminary data update are raised. During the following week, potential equation changes are proposed, tested, documented, and then implemented through a regulated process that occurs through the coordination of members of the Model Development and Forecast Operations teams.

As part of every equation update, the full model is test solved for both a straight baseline forecast as well as a set of sample scenario shocks, using only exogenous drivers. Model solves and evaluation are done without inclusion of analyst add-factors, to isolate the performance of the model alone. 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 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 a great deal, but in a way uncorrelated with changes in real GDP. Such issues are typically flagged, but assigned a "low priority" indicating that a better performing equation is still desired, but it is understood that no superior alternative is immediately available.

In some smaller, lower-income countries, data constraints, mismeasurement of concepts arising from a large informal share of the economy, and volatile or highly inflationary macroeconomic conditions complicate greatly the construction of a complete, fully linked, flexible and 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—many of them in Africa, the Middle East, and Central Asia—will remain a work in progress, with the models evolving along with economic conditions and improvements in data availability

4 Cross-validation techniques can be used, which involve re-estimating equations on a limited sub-sample of the data (for example, estimating using data up to 2009, to test forecasts for 2010-2017 against available history), but re-estimating on a subsample of data often changes coefficients in a way that affects the forecast performance. Ultimately, therefore, cross-validation amounts to a good test, but of the wrong model.

and concept coverage. In the meantime, the forecast models serve as valuable toolkits 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 a 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 (FRGT10Y). 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, 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 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 discounting behavior.

Appendix 1: "Template" equation specifications for initial model estimation for each country

» **Unemployment rate (model mnemonic FLBR).** The unemployment rate is 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 forecast 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 assumption.

» **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 proxied 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 naive trend, in accordance with the budgeting process. Government expenditures and tax rates are assumed to be largely exogenous, with values overridden 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 industry, the depth and maturity of domestic financial markets as well as the exposure to global capital markets, different levels of volatility and risk aversion, and the standard nature of corporate financing. In most cases, however, investment is modeled as a function primarily of expected growth, prevailing interest rates, and Tobin's Q, which is the ratio of equity value of capital to the book value of replacement. In commodity-exporting countries, global oil prices are used as a proxy for improved profitability, while in large net energy importing countries, oil 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 (FTFXTWS_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 (FTABGDP_T_IGEO).

» **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 a 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 (FRGT10Y).** 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, 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 (FTFXTWS) 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 (FTFXTWS_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 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 discounting behavior.

Appendix 2: Examples of top-down/bottom-up equation specifications

- A coincident economic indicator (FCEI_IEUZN) is a 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 (FGDP$_IEUZN). In this way, FCEI_IEUZN is used as a "lever" to generate a forecast FGDP$_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$_I) reflects a country's predicted real effective exchange rate (REER). In floating rate countries, this represents the primitive for exchange rate forecasts; it is a mean-reverting forecast that varies with interest rates, expectations, commodity prices, the predicted strength of the U.S. dollar, and other factors known to influence interest rates. From this series, bilateral foreign exchange rates can be computed against the dollar, and from this, bilateral cross-rates. Using bilateral cross-rates and CPI forecasts, an ex-post REER (the series FTFXTW$) is calculated as an aggregate.

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$_US—Real GDP.
- FCPIU_US—Consumer price index.
- FPGDP_US—GDP implicit price deflator.
- FTFXBRD$_US—Real weighed average exchange value of U.S. dollar: Broad index (this drives foreign exchange rates, that then feed back to the REER FTFXTW$_IUSA).
- FCPWTI_US—West Texas Intermediate price of crude oil (this drives Brent oil, which forms the basis for FPCPOILSQ.IWRLD, or real global oil prices).
- FRFED_US—Federal funds rate.
- 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.
- FRLIBOR3M_US—LIBOR, which is used as a spread vs. FRGT3M_US.
- FRBAAC_US—Moody's Baa corporate bond yield, used as a level and as a spread vs. FRGT10Y_US.
- FSP500Q_US—S&P 500 Composite Price Index.
- FSPVOL_US—S&P 500 Volatility.
- 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.
- FCPIHXAQ_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.

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