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Moody's Analytics Global National Forecast Methodology

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Abstract

Each Moody's Analytics international country model is a system of simultaneous equations producing an average of 80 forecast variables and six scenarios. Currently, forecasts are updated each month for more than 50 countries plus the euro zone.

This article begins with a brief discussion of the objectives for creating the country models. It then discusses the various methods of macroeconomic forecasting with an emphasis on the Moody's Analytics approach to forecasting. This is followed by a detailed explanation of the model methodology. The next section provides details of model construction and gives an example to illustrate the model-building process. In the following section, key features of the model are highlighted using various examples. To conclude, the article provides an assessment of forecast accuracy tests of the Moody's Analytics models against other forms of models. An appendix provides a list of the key forecast variables included in each country model.

Moody's Analytics Global National Forecast Methodology

BY SUNAYANA MEHRA

Each Moody's Analytics international country model is a system of simultaneous equations producing an average of 80 forecast variables and six scenarios. Currently, forecasts are updated each month for more than 50 countries plus the euro zone.

This article begins with a brief discussion of the objectives for creating the country models. It then discusses the various methods of macroeconomic forecasting with an emphasis on the Moody's Analytics approach to forecasting. This is followed by a detailed explanation of the model methodology. The next section provides details of model construction and gives an example to illustrate the model-building process. In the following section, key features of the model are highlighted using various examples. To conclude, the article provides an assessment of forecast accuracy tests of the Moody's Analytics models against other forms of models. An appendix provides a list of the key forecast variables included in each country model.

Model objectives

The equations of each country model are estimated for each country beginning with a standard template for a simultaneous equation model, encompassing the entire macro economy of the country. Standardization makes cross-country comparisons possible, but it also affords some flexibility that allows Moody's Analytics to bring in nuances relevant to each country. Our country models are updated monthly and project economic activity for up to 10 years ahead under baseline and alternative scenario assumptions.

The forecast models are intended to have broad appeal across users from different industries such as commercial real estate, electric utilities, government agencies, financial services, and retailing to name a few. Macroeconomic forecasts help consumers, firms and governments make better decisions.

Businesses use macroeconomic analysis to make key investment decisions such as timing for expanding production or venturing into new markets. Good long-term forecasts of factors such as consumer spending, interest rates and employment conditions can improve project assessment and reduce the chances of future surprises.

Financial institutions use macroeconomic forecasts to gauge the health of their outstanding loan portfolios as well as lending conditions.

Policymakers need forecasts to project the likely path of important economic indicators such as inflation, output or unemployment given key assumptions such as monetary policy. They can also use macroeconomic forecasts to be able to shape key fiscal variables such as tax rates or government spending depending on the growth trajectory of the economy.

Finally, a growing need for most macroeconomic models is to be able to deliver on scenario analysis. The Moody's Analytics country models have been designed to facilitate analysis of what-if questions such as oil price shocks, a housing bust or boom, high or low interest rates, or even natural disasters. Scenario analysis is useful for stress-testing portfolios, forming contingency plans, and evaluating the impact of shocks.

The Moody's Analytics global forecast system satisfies the following requirements:

- The system is comprehensive so that the countries covered add up to more than 90% of global GDP (see Table 1).
- Forecasts are produced for an average of 80 key variables (see Appendix) that are critical for gaining insight into a country's macro economy. Further, the models are capable of being supplemented with additional variables to accommodate client needs.
- The system is built on solid economic theory and econometric methods and reflects recent progress in advanced macroeconomic forecasting.
- The models have good statistical properties, are robust in tests, and most importantly, have good forecast capabilities.

The system draws extensively from the modern literature of macroeconomic forecasting and takes advantage of the rich data sources at Moody's Analytics. As a fundamentals-based forecast system, all of its equations have good econometric properties and performed well in a series of backcast tests.

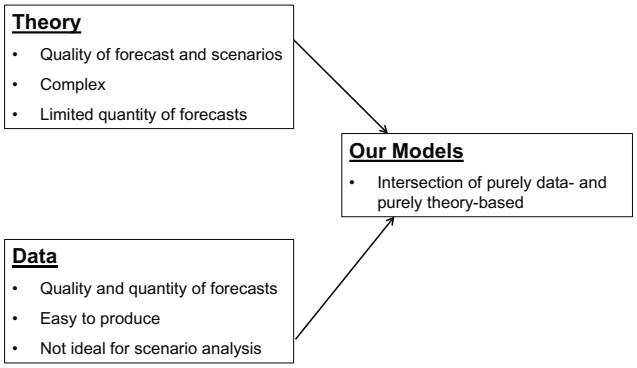
Model philosophy

The global national macroeconomic forecast models are structured for three dis-

Table 1: Country Forecast Models Available as of Dec 2012

North America	**Eastern Europe**
Canada	Czech Republic
Mexico	Hungary
South America	Poland
Argentina	Russia
Brazil	Turkey
Chile	Oceania
Colombia	Australia
Peru	New Zealand
Venezuela	**Middle East/Africa**
Euro Zone	Israel
Austria	South Africa
Finland	**Asia**
France	*Developing Asia*
Germany	China
Greece	India
Ireland	Indonesia
Italy	Malaysia
Netherlands	Philippines
Portugal	Thailand
Spain	*Developed Asia*
Slovakia	Japan
Slovenia	South Korea
Belgium	Singapore
Luxembourg	Taiwan
Other Western Europe	Hong Kong
Denmark	
Norway	
Sweden	
Switzerland	
U.K.	

Chart 1: Approach to Forecasting



tinct purposes: to forecast future values of key economic variables such as GDP, interest rates and inflation; to explain the causality between various aspects of the macro economy based on theoretic a priori; and to produce counterfactuals and undertake scenario analysis based on the relationships established between variables.

The most common types of econometric models used in macroeconomic forecasting today fall into three broad categories: structural, nonstructural and hybrid models (see Chart 1).

Structural models are built using the fundamental principles of economic theory. Examples are general equilibrium growth models such as real business cycle and dynamic stochastic general equilibrium models. Highly entrenched in economic theory, the economy is modeled as a production function, decisions are made by constrained optimization, and many assumptions about theory are required, making general equilibrium models a resource-intensive method of producing forecasts. DSGE models can be difficult to solve and analyze, are small in scale, and cannot easily incorporate the large array of high-frequency data usually available to policymakers, leading to possible misspecification. DSGE models have been characterized as useful story-telling devices that cannot yet replace large-scale models for forecasting purposes.[1]

Nonstructural models are primarily statistical time-series models—that is, they represent correlations of historical data. They incorporate little economic structure, which gives them enough flexibility to capture the force of history in the forecasts they generate. Vector autoregressive models are an example of purely data-driven models that are relatively easy to build and to use for forecasting. But there are costs associated with being free from any theoretical underpinnings that make statistical models less suitable for simulating economic processes and generating scenarios.

While Moody's Analytics acknowledges the forecast capacities of pure time series analysis, the Moody's Analytics system—a sample of the hybrid approach to modeling—does not take such a black-box approach for two reasons. First, many users need to know the forces behind the projected trends. The pure time series mean-reversion approach would say that history creates a trend that will persist into the future; short-term fluctuation along the trend would be due to propagation of unknown shocks. Any further reasoning based on economic fundamentals—such as, for example, that a downturn in exports is due to a slowdown in a country's main trade partners—would be based on an analyst's conjecture rather than the model. Second, long-term trends do shift over time, so forecasts relying on the preservation of current trends are more difficult to defend. When a trend shift does happen, it may take a long time before one can econometrically establish the trend shift in a time series model.

1 See Sims, Christopher, Comment on Del Negro, Schorfheide, Smets, and Wouters, Journal of Business and Economic Statistic, 2006.

Other purist time series modeling methods such as ARIMA, following Box and Jenkins (1976), also have not been adopted for the Moody's Analytics global forecast system because of their black-box approaches.[2]

The Moody's Analytics forecast system is a hybrid system based on economic fundamentals. In general, it follows the so-called Cowles Commission approach.[3] In this approach, economic theories or intuitions play a key role in guiding the selection of explanatory variables.

The Moody's Analytics approach, similar to that of fundamentals-based models, is a system of simultaneous equations that is a good compromise between the purely theory-driven general equilibrium model and the purely data-driven VAR model. The models are like nonstructural models in that they are built from many equations that describe relationships derived from empirical data. They are like structural models in that they also use economic theory. Moody's Analytics forecasts are simulations of a series of dynamic equations where regressions are used to estimate coefficients based on historical relationships and theoretical a priori.

Further, to keep the system tenable and yet still provide a detailed forecast system, Moody's Analytics has constructed the models by breaking them into two sections: a small simultaneous core set of variables and a second set of auxiliary variables that are driven by the core set of variables. The advantage of such a system is that it can be large and yet easy to maintain.

Through research of the historical relationships between macroeconomic concepts, and by using rigorous forecast accuracy checks, the Moody's Analytics models are able to deliver forecasts that provide a good baseline for the short- and long-run outlooks, as well as desirable shock properties for scenarios.

Constructing the models

Variables. To be able to generate a large-scale forecast system that is suitable for a variety of purposes yet remains manageable, Moody's Analytics decomposes its variables into various segments. The model has a standard set of exogenous variables. Exogenous variables are typically forecast outside the country model and are starting points of the forecast process. These are also key sources where shocks could originate. Global GDP, the European Central Bank monetary policy rate, population growth, and global energy prices are typical exogenous variables in the model.

Endogenous variables of the model may be considered either core variables or tailpipe variables. Core variables are the model's most important and decisive variables such as consumer spending, CPI, the unemployment rate, exports, and the exchange rate. Core variables are typically driven by other core and/or exogenous variables. Core variables can also take the form of identities to preserve macroeconomic relations. For instance, GDP is an identity equal to the sum of its components—consumption, investment, government spending and net exports. Tailpipe endogenous variables are a model's second-tier variables that complete the architecture of the macro economy of a country. To create a manageable model that is easy to re-estimate and control, tailpipe variables are driven by core and/or exogenous variables but do not become drivers for core variables. Examples include the lending rate and the GDP deflator. Tailpipe variables can also take on the form of identities such as nominal GDP.

During model estimation, the equations are specified according to our understanding of demand, supply, and special events that may have occurred during the period of the historical data. The sampling period is carefully chosen so that valid statistical inference can be made. Then the equations are estimated and selected according to their statistical properties. Since all Moody's Analytics equations are based on economic fundamentals, understanding of a country's macro economy heavily influences the variable selection and equation specification.

Theoretical priors. All Moody's Analytics models are developed based on the workings of an open macro economy, so that their structure is fairly standard. Nevertheless, Moody's Analytics pays careful attention to country-specific macroeconomic nuances when necessary and weaves them into the models.

The level of development of a country's macro economy determines the composition of the main aggregate demand and supply variables. Whereas private consumption is the largest component of aggregate demand in almost all countries, the composition of consumer spending differs. For instance, in most developed countries such as the U.S. the marginal propensity to consume out of wealth[4] tends to be much higher relative to developing countries and emerging markets such as Brazil. Consumers in developing economies rely mostly on wages and salaries to make consumption decisions.

Trade is another key factor that is explicitly factored into the model structure. Most countries trade within the vicinity of their region, and such trade patterns are supported by regional trade agreements. This is evident across Europe, where most countries of the European Union have a high share of their trade with other EU nations. Similarly, because of proximity and a free trade agreement between North American countries, Mexico has an above-average share of exports headed to the U.S. and Canada. At the same time, most emerging economies such as China trade globally. Such trade linkages are factored explicitly into each country's model structure. The models for euro zone countries differ slightly from the standard country models. Countries using the euro do not have their individual central bank monetary policy rates; instead, the monetary policy rate set by the ECB is treated as an exogenous variable. Similarly, the exchange rate for euro zone countries is determined in the Moody's Analytics euro zone model and is an exogenous variable in the individual euro zone country models.

Specifications. The Moody's Analytics forecast system borrows actively from the time series literature. For instance, many Moody's Analytics equations have lagged

2 See Box, G.E. and Jenkins, G.M. Time Series Analysis: Forecasting and Control, Holden-Day, 1976.

3 For a detailed discussion of the approach and its application, see Fair, R.C., Testing Macroeconometric Models, Harvard University Press, 1994.

4 Wealth is proxied by stock market movements and house price trends.

auto-regressive terms and are thus mixed models. Moody's Analytics also uses co-integration and error correction methods when appropriate. Many alternative specifications can be used to model a variable's historical relationship with its drivers. The most frequently assumed form is

$$\Delta log(y_t) = \sum_{i=1}^{I} \beta_i \Delta log(y_{t-i}) + \sum_{k=1}^{K}\sum_{j=1}^{J_k} \gamma_j^k \Delta log(x_{t-j}^k) + u_t, \quad (1)$$

in which y_t is the dependent variable in quarterly frequency at time t and Δ is a difference operator. x_t^k is the value of kth fundamental driver at time t. The order of lags for I and J_k are usually very low.[5]

Cointegration[6] regression is occasionally used when there is sufficient statistical evidence for the assumed form of the data generation process.

$$log(y_t) = \alpha + \sum_{k=1}^{K}\sum_{j=0}^{J_k} \gamma_j^k log(x_{t-j}^k) + u_t. \quad (2)$$

If there is no economic intuition or evidence that a variable and its driver are cointegrated, it is estimated through equations such as (1) or (2). If, however, it is found that a variable and its driver were growing at the same speed, the following form is used to impose a restriction of equal growth rates when it is justified by both economic intuition and statistical evidence

$$\Delta log(z_t) = \sum_{i=1}^{I} \beta_i \Delta log(z_{t-i}) + \sum_{k=1}^{K}\sum_{j=1}^{J_k} \gamma_j^k \Delta log(x_{t-j}^k) + \delta(\log(z_{t-1}) - \log(y_{t-1})) + u_t, \quad (3)$$

in which y_t is the explanatory variable that is deemed to be growing at the same rate as z_t. The term $\delta(\log(z_{t-1})-\log(y_{t-1}))$ is the "error correction term" in a vector error correction model. The estimated has to be negative to guarantee the same asymptotic growth speeds of z_t and y_t.

Model selection. The model for each country is composed of a set of equations. For each equation in the model, Moody's Analytics always comes up with a handful of potential alternative specifications. The right-hand-side variables in all equations are generally significant at the 5% level. That said, if Moody's Analytics has very strong priors that a certain additional independent variable drives a dependent variable's growth, it is willing to put it in the equation even if the corresponding p-value is slightly above 5%.

Once complete, each alternative specification for an equation is then analyzed based on statistical properties such as adjusted R-square, significance level, Durbin-Watson statistic, backcast performance, judgmental evaluation of short-term forecasts, and long-term performances. The evaluation of backcast performances are based on root mean squared error, root absolute error, and Theil Inequality coefficients. Another important criterion in finalizing the global models is parsimony. When two equations are roughly the same based on statistical criteria, those with fewer variables are usually selected. Such a practice is meant to avoid the common mistake of overfitting. When much effort is made to pick the "best" model, one may start to include too many explanatory variables to fit the movement of random errors. While statistical criteria help select the best specification for the Moody's Analytics equations, the parsimony principle is applied with judgment.

During the specification selection process, the stability of the equation system is checked by looking at the characteristic roots and other mathematical properties. Once the equations are finalized, a country's forecast model is shocked with different scenarios of exogenous or endogenous variables. The scenario shocks are used to ensure the response of systems to impulses are within a reasonable range.

Understanding the model: An example of the United Kingdom

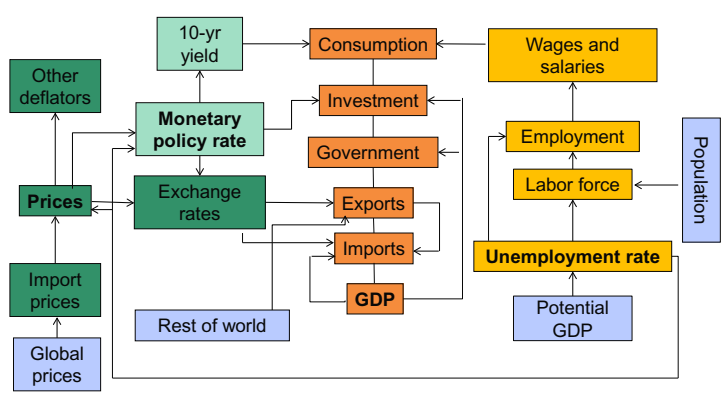
In this section, a particular country model is elaborated on to detail the model structure and forecasting methodology while highlighting certain nuances of the econometric process that were outlined in the previous section. The U.K. model will serve as an example. The U.K. is the sixth largest economy in the world and the third largest in Europe. The U.K. also has the largest offering of data (after the U.S.) among all countries in the Moody's Analytics data catalog, making it one of the most detailed models and an obvious choice for an example.

The model's core equations are a small set of variables that drive the rest of the model. The core variables include:

- aggregate demand (GDP)
- trade
- labor market
- prices
- monetary policy
- housing

These core variables interact with each other to form a simultaneous system of equations (see Chart 2).

Chart 2: Model Design



5 In the case when I equals 1, we have a familiar "distributed lag" model with straightforward interpretation of coefficients.

6 If two or more series are individually integrated (in the time series sense) but some linear combination of them has a lower order of integration, then the series are said to be cointegrated. For example, the price of a stock and the dividend paid on it.

Table 2: Private Consumption of Goods and Services, U.K.

Dependent variable:	DLOG (private consumption of goods and services per person)
Sample (adjusted):	1999Q2-2012Q2
Included observations:	53 after adjustments

R-squared	0.5898
Adjusted R-squared	0.5549
Durbin-Watson stat	1.9974

Variable	Coefficient	t-Statistic
Interest rate	-0.0023	-0.7271
DLOG (real wages & salaries per person)	0.5295	2.5857
DLOG (house prices)	0.1486	3.9967
DLOG (stock market value)	0.0255	1.8164
DLOG (oil prices, 3-qtr MA)	-0.0024	-0.2888

DLOG refers to the simple difference of a natural logarithm

In the broadest sense, aggregate economic activity is determined by the intersection of the economy's aggregate demand and supply functions. In the short run, fluctuations in economic activity are primarily determined by shifts in aggregate demand. The level of resources and technology available for production are taken as a given. Prices and wages adjust slowly to equate aggregate demand and supply. In the long run, changes in aggregate supply determine the economy's growth potential. The rate of expansion of the resource and technology base of the economy is the principal determinant of the pace of economic growth.

Aggregate demand. The aggregate demand schedule is the sum of consumption, investment, international trade and government spending.

(Demand = Consumption + Investment + Government + Net Exports)

This is one of the most pivotal macroeconomic identities that is true to every country and the model structure preserves this key relationship between final demand variables in the forecast.

Real consumption is modeled on a per capita basis to account for population growth. The most important variable that drives consumption is real disposable income. That said, real wealth is also an important variable that dictates private consumption, especially in developed economies such as the U.K. For this reason, a measure of the wealth effect is included as gauged by movements in house prices and the stock market.[7]

While real disposable income and real wealth are the long-term determinants of consumption, changes in the real interest rate account for short-run fluctuations in real consumption. Interest rates are typically the opportunity cost of consumption, but because interest rates are not high in the U.K. at this time, the effect is small compared with India, for example, where high interest rates induce individuals to save instead of spend. Finally, energy prices or inflation expectations also impact real consumption of vehicles, nondurable goods and services. However, this effect is negligible for most Western European countries such as the U.K. The consumption function for the U.K. is summarized in Table 2. Chart 3 shows the residual plot of the historical fit of the consumption series.

Gross domestic investment is divided into private investment and inventories. Fixed business investment plays an important role in both the demand and supply sides of the economy. In traditional accelerator/multiplier theory,[8] the level of investment depends on the change in expected output; investment changes will in turn stimulate further movements in output through the multiplier effects.[9] For the U.K., this effect is strong. Aviation equipment and automobile manufacturing are among the largest industries in the U.K. and they tend to be capital intensive. Because these industries are procyclical, investment in the U.K. has the potential to intensify upswings and downswings in the business cycle. Following the accelerator/multiplier approach, net investment is modeled as a function of changes in expected output and the cost of capital as proxied

Chart 3: Residual Plot—U.K. Private Consumption

Private consumption per person, residual (L), actual and fitted (R)

Note: See Table 2 for the equation for private consumption per person.

7 According to the wealth effect, people should spend more when people perceive themselves to be richer—for example, the assessed value of their home increases, or a stock they own goes up in price.

8 P. Samuelson. "Interaction Between the Multiplier Analysis and the Principle of Acceleration," Review of Economic Statistics (May 1939).

9 The accelerator effect refers to a positive effect of GDP growth on private fixed investment. Rising GDP implies that businesses in general see rising profits, increased sales and cash flow, and greater use of existing capacity. This prompts businesses to build more factories and install more machinery. This may lead to further growth of the economy through the stimulation of consumer incomes and purchases—that is, via the multiplier effect.

by an appropriate interest rate. Corporate cash flow and debt levels are also important determinants in the investment equations. These are approximated by movements in the stock market (see Table 3).

Government spending is a function of government revenue. Total government revenue is the sum of personal tax receipts, social insurance contributions, corporate profit tax receipts, and indirect tax receipts that are a function of total economic activity. The budget deficit is defined as the difference between government revenue and expenditure.

Trade. The Moody's Analytics global models include an international trade sector that captures the interactions between foreign and domestic prices, interest rates, exchange rates, and product flows. Export prices and volumes are determined by stochastic equations, while nominal trade flows are calculated as identities. The key determinants of a country's export volumes are relative prices and a weighted average of the GDP growth rate of trading partners, captured in a trade weighted global GDP term.

Weights are based on the geographic distribution of the country's exports. For most countries, demand for exports is measured using the trade weighted global GDP term, but for some countries, Moody's Analytics opts to use GDP of their major trade partners. For example, using global GDP is good idea for a country such as Thailand that exports auto parts to almost all countries. But for the U.K., it is more appropriate to just use euro zone GDP. The U.K.'s main trade partner is the euro zone. Some 58% of the U.K. exports go to euro zone nations. In addition, euro zone countries provide upwards of 53% of U.K. imports.

The specification for imports of goods and services is richer than that for exports. Real imports are determined by specific domestic spending categories and relative prices. In the case of countries where the import content of exports is particularly high, export volumes also are used as an explanatory variable. This is true for the U.K. and such a pattern of trade is evident via the British automobile industry. Vehicles other than railway or tramway rolling-stock, and parts and accessories thereof, ranked as both the third highest import and export in 2011. Import prices are captured via the exchange rate converted into local currency (see Table 4).

Table 3: Gross Fixed Capital Formation, U.K.

Dependent variable:	DLOG (gross fixed capital formation)
Sample (adjusted):	1999Q2-2012Q2
Included observations:	53 after adjustments

R-squared	0.363805
Adjusted R-squared	0.338358
Durbin-Watson stat	2.420897

Variable	Coefficient	t-Statistic
Interest rate	-0.08254	1.640146
DLOG (real GDP, lag 1)	1.155281	3.24079
DLOG (stock market value)	0.114907	2.400624

DLOG refers to the simple difference of a natural logarithm

Table 4: Imports of Goods and Services, U.K.

Dependent variable:	DLOG (import of goods and services)
Sample (adjusted):	2000Q2-2012Q2
Included observations:	49 after adjustments

R-squared	0.298428
Adjusted R-squared	0.251657
Durbin-Watson stat	2.046874

Variable	Coefficient	t-Statistic
Constant	0.001814	0.420369
DLOG (domestic demand of goods and services, lag 1)	1.549339	3.69053
DLOG (export of goods and services, lag 1)	0.025827	0.237817
DLOG (exchange rate: USD/GBP)	0.178686	2.283358

DLOG refers to the simple difference of a natural logarithm

The U.K.'s pound sterling is the world's third largest reserve currency after the U.S. dollar and the euro. The local currency/dollar exchange rate is determined endogenously. The dependent variable is the ratio of local to foreign price levels, so that the exchange rate fully reflects changes in relative prices. In addition to country-specific price levels, another determinant of the real exchange rate is the differential between local and foreign interest rates.

Labor market. The supply side of the country model describes the economy's capabilities for producing output. In the model, the labor market and the potential GDP growth rate make up the supply side. Potential GDP growth is determined exogenously using a Hodrick–Prescott filter[10] technique that separates the long-term trend in GDP growth from business cycle activity. The HP filter is a mathematical tool used in macroeconomics, especially in real business cycle theory to separate the cyclical component of a time series from raw data. It is used to obtain a smoothed-curve representation of

10 Hodrick, Robert, and Edward C. Prescott (1997), "Postwar U.S. Business Cycles: An Empirical Investigation," Journal of Money, Credit, and Banking, 29 (1), 1–16.

Table 5: Labor Force, U.K.

Dependent variable:	LOG (labor force share of population)
Sample (adjusted):	1991Q2-2012Q2
Included observations:	85 after adjustments
R-squared	0.988323
Adjusted R-squared	0.988024
Durbin-Watson stat	1.874617

Variable	Coefficient	t-Statistic
Constant	-0.011078	-1.252141
LOG (working-age share of population, 15 to 64 yrs)	0.324049	7.412846
LOG (lagged dependent variable)	0.789424	25.38824

Table 6: Consumer Prices, U.K.

Dependent variable:	LOG (consumer price index)
Sample (adjusted):	1998Q1-2012Q2
Included observations:	58 after adjustments
R-squared	0.910751
Adjusted R-squared	0.907445
Durbin-Watson stat	2.220897

Variable	Coefficient	t-Statistic
Constant	0.397632	1.408841
LOG (implicit price deflator: import of goods and services)	0.939113	15.06888
Unemployment rate-NAIRU	-0.024038	-3.959147

a time series, one that is more sensitive to long- than to short-term fluctuations. The potential GDP term is a key determinant of the unemployment rate, the most important supply side variable in the model.

The unemployment rate in the economy depends on the difference between the growth rate of GDP and the exogenously determined potential GDP growth rate. In addition, two other aspects of the labor market are also modeled (see Table 5). First, the labor force is a function of the working-age population in the country. Second, the level of employment is solved using the labor force and the unemployment rate. With these solved, total wages and salaries are determined as a function of the level of employment and the wage rate in the economy.

Prices. Firms set their prices with the prices of their inputs in mind. And firms also adjust their prices in response to conditions in their markets. If demand has been strong and firms are producing more than they think is appropriate given their current prices, they will raise their prices. If demand has been weak, firms will lower their prices. When looking at this process in terms of aggregate variables—GDP and the price level—prices will tend to rise whenever GDP has been above potential and will tend to fall when it has been below potential.

Consumer prices are the key price variable that is a part of the model's simultaneous core. Consumer prices are forecast based on the Phillips curve, which postulates a historical inverse relationship between the rate of unemployment and the rate of inflation in an economy. Explanatory variables in the price equation include the difference between the actual unemployment rate and NAIRU[11] and a lag on import price deflator. Import price deflators, for example, are direct determinants of many of the indexes for consumption goods. The consumer price equation reflects the objective of the modeling process of keeping the forecast models as close to theoretical priors as possible (see Table 6).

Producer prices in the model are driven by lagged consumer prices and import prices. The price deflators in the model, with the exception of imports, are driven by producer, consumer and import prices.

Import price deflators are direct determinants of most of the deflators for consumption goods and are determined by oil prices and global prices expressed in local currency.

Financial sector. The Bank of England's Monetary Policy Committee sets short-term interest rates. The committee is responsible primarily for keeping the consumer price index measure of inflation close to a target set by the government, and it does so by using monetary policy. The financial sector of the model is composed of equations for money demand, and short- and long-term interest rates. The money demand equations are derived from portfolio theory, in which the demand for cash depends on the level of income, the expected level of transactions, and the opportunity cost of holding liquid assets as opposed to other interest-earning instruments.

The key short-term rate in the model is the central bank's policy rate. The policy rate equation is based on a Taylor rule-like reaction function.[12] This approach is consistent with most central banks in the world. Monetary policy in the model is primarily guided by economic conditions

11 NAIRU (Non-Accelerating Inflation Rate of Unemployment) is the unemployment rate consistent with steady price (and wage) inflation. It is also the unemployment rate at which actual GDP equals potential GDP. This level is derived from a measure of potential labor supply and a measure of the long-run equilibrium unemployment rate.

12 The Taylor rule is a central bank reaction function that computes an optimal policy rate using the real interest rate, the desired rate of inflation, and deviations in inflation and economic output from their targets. Developed by Stanford economist John Taylor, the Taylor rule has been used as an important reference point for policymakers as they craft monetary policy.

and the prospects of inflation (see Table 7). It is worth noting that the sample for this regression ends in 2008. This is an instance where sample selection is based on special events. Toward the end of 2008, there was growing evidence that the U.K. economy was rapidly heading into recession. As a result, from October 2008 to March 2009, the Bank of England's base rate was cut six times to an all-time low of 0.5% in order to avoid deflation and spur growth. In March 2009, interest rates had fallen to historic lows rapidly as a result of temporary programs, and so the MPC launched a program of quantitative easing, initially injecting £75 billion into the economy.[13] By ending the period of regression estimation in 2008, this period of extraordinarily low interest rates was avoided when computing coefficients for the interest rate equations in the U.K.

The most important long-term interest rate in the model is the 10-year bond yield, which is modeled as a function of factors closely followed by bond investors. These include indicators of current economic conditions, expectations of the future national budget deficit, and the term structure of the monetary policy rate. These factors are pivotal in determining inflation expectations of bond investors, making them relevant to the long-term interest rate forecast (see Table 8). As with the interest rate block of equations, the sample period is shortened, ending in 2008.

Housing. Most developed countries experienced sharp increases in house prices through the middle to later years of the 2000s. The U.K. housing market was no exception, and its regional pattern was fairly uniform. From 2002 to 2008, house prices in the U.K. rose by 90%, faster than any EU nation except Spain.[14] In the Moody's Analytics model, house prices are specified as a function of factors that influence both the demand and supply of homes (see Table 9). Demand for homes depends on income, the jobless rate, after-tax borrowing costs, and credit availability. Income per household measures both the ability and willingness of households to purchase a home. Rising income levels will result in increased homebuying. The jobless rate also determines consumers' willingness to buy. If a high jobless rate drives consumer confidence lower, homebuying will remain lackluster even if income levels are rising.

The variables highlighted in this section make up the simultaneous core of the U.K. model. The remaining variables constitute tailpipe variables and are modeled based on combinations of these core variables.

Table 7: Official Discount Rate—Bank of England, U.K.

Dependent variable:	Official discount rate
Sample:	1998Q1-2008Q4
Included observations:	44 after adjustment
R-squared	0.2036
Adjusted R-squared	0.1647
Durbin-Watson stat	1.2938

Variable	Coefficient	t-Statistic
Constant	-0.0214	-1.4216
Unemployment rate-NAIRU	-0.2195	-3.2359
DLOG (consumer price index)	0.7998	0.3746

DLOG refers to the simple difference of a natural logarithm

Table 8: 10-Yr Discount Bond Yield, U.K.

Dependent variable:	10-yr discount bond yield
Sample (adjusted):	1995Q4-2008Q4
Included observations:	53 after adjustments
R-squared	0.5698
Adjusted R-squared	0.5454
Durbin-Watson stat	0.4020

Variable	Coefficient	t-Statistic
Constant	1.357123	2.8712
Monetary policy rate	0.572904	5.057292
% change (GDP, 2-qtr MA)	7.565721	0.992069
4-qtr MA (government budget balance as share of GDP)	-23.87578	-4.98354

DLOG refers to the simple difference of a natural logarithm

Key model features

Fundamentals matter. The Moody's Analytics fundamentals-based approach to forecasting aims to specify equations similarly across all country models. The specification of the equation for the 10-year yield for Germany is fairly representative of this approach. The equation system considers the key policy rate, economic conditions, and inflation prospects, as well as nominal GDP growth and the government's fiscal balance, to estimate an interest rate that corresponds to fundamentals

13 "Bank of England Adds 75 billion to Quantitative Easing Program". Central Bank News. 6 October 2011. http://www.centralbanknews.info/2011/10/bank-of-england-adds-75-billion-to.html

14 Chamberlin, Graham (August 2009), "Recent developments in the UK housing market", Economic and Labour Market Review 3 (8): 29–38, http://www.statistics.gov.uk/elmr/08_09/downloads/ELMR_Aug09_Chamberlin.pdf

Table 9: House Prices, U.K.

Dependent variable:	DLOG (avg nominal house price)
Sample (adjusted):	1996Q1-2012Q2
Included observations:	67 after adjustments

R-squared	0.178515
Adjusted R-squared	0.139397
Durbin-Watson stat	1.523638

Variable	Coefficient	t-Statistic
Constant	0.011685	2.920183
DLOG (mortgage interest rate)	-0.142262	-3.003022
DLOG (real disposable income, lag 1)	0.081385	0.32255
DLOG (unemployment rate, lag 1)	-0.216926	-2.610416

DLOG refers to the simple difference of a natural logarithm

(see Chart 4a and 4b). This simulation based on theoretical a priori and fundamental drivers provides a good historical fit for Germany, and for most other countries. But changes are made to specifications where necessary. For example, the fundamentals-based historical fit with a specification similar to that for Germany misses the mark for Italy. Comparing long-term yields to their historical values, it is evident that yields in the euro zone's troubled economies such as Italy have risen above those that could be justified by weak fiscal and macroeconomic fundamentals alone. Sovereign yields increasingly reflect investor sentiment, including perceptions of the risk of a euro zone breakup, aspects that are hard to capture using macroeconomic fundamentals. This is also the reason why crisis-like situations sometimes create plausible deviations between a model's simulation and actual data (see Table 10).

Core and tailpipe variables. Another feature of the model is the relation between core and tailpipe variables. Core variables are the model's most important and decisive variables that are driven simultaneously by other core and/or exogenous variables. Examples illustrated in the description of the U.K. model include consumer prices, the unemployment rate, and fixed investment. The tailpipe variables are the model's second-tier or auxiliary variables that are driven by core and exogenous variables. But they do not become drivers for core variables. Some examples are various price deflators and industrial production, among many others.

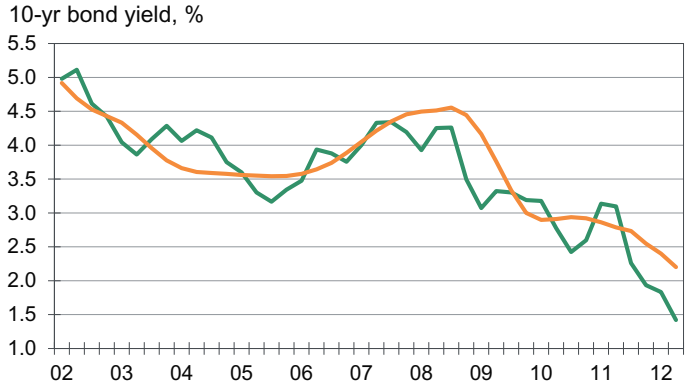
Modeling auxiliary variables as a function of the core set of equations is an approach that makes it easy to re-estimate and control the forecast system. In addition, it also provides the capacity to build a large catalog of forecast variables without compromising the quality of key variables (see Chart 5). The monetary policy rate is an example of the relationship between core and auxiliary variables. Such a relationship holds true for all Moody's Analytics models—the instance of Sweden is shown here as an example. Based on their historical relationship, it is found that the lending rate, the rate at which financial institutions lend money, and the money market rate, a key short term interest rate for maintaining liquidity in the economy, track the monetary policy rate that is set by the central bank almost one on one.

With this historical relationship in mind, it is easy to predict that the forecast for the lending rate and the money market rate will follow the same trajectory as the monetary policy rate, which is the exact specification that all models use. Such an approach allows there to be multiple interest rates without compromising the quality of the forecast of the central bank's key interest rate.

Similar examples can also be seen regarding prices. More attention is paid to consumer prices, and the consumption deflator is made to follow consumer prices.

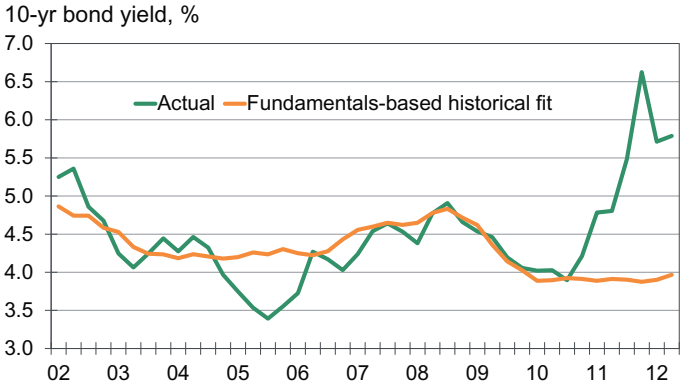
Standard template. A standard template of equations is used in specifying models for all countries, and thus the estimated regressions used to forecast the key variables look similar for all of the country models. This

Chart 4a: Fundamentals Matter: Germany



Sources: International Monetary Fund (IMF), Moody's Analytics

Chart 4b: Fundamentals Matter: Italy



Sources: Central Bank of Italy, Moody's Analytics

Table 10: Fundamentals Matter

Dependent variable: 10-yr yield

	Germany		Italy	
Sample (adjusted):	2000Q1-2012Q1		2000Q4-2012Q2	
Included observations:	52 after adjustments		48 after adjustments	
R-squared	0.6026		0.4452	
Adjusted R-squared	0.5755		0.4026	
Durbin-Watson stat	0.4020		0.4229	
Variable	Coefficient	t-Statistic	Coefficient	t-Statistic
Constant	1.850484	5.095945	3.194657	4.414658
Monetary policy rate	0.67603	7.32807	0.35867	3.31131
% change (GDP, 2-qtr MA)	0.460633	0.131284	1.639309	0.435124
4-qtr MA (government budget balance as share of GDP)	-39.08733	-1.679355	-28.2117	-0.525443

Table 11: Standard Template: All (Consumption) Functions Are Created Equal

DLOG (real consumption of goods and services per person)

	Netherlands		South Africa	
Sample (adjusted):	1997Q2-2012Q1		1996Q1-2012Q2	
Included observations:	61 after adjustments		66 after adjustments	
R-squared	0.5110		0.5991	
Adjusted R-squared	0.5047		0.5728	
Durbin-Watson stat	1.9974		1.2529	
Variable	Coefficient	t-Statistic	Coefficient	t-Statistic
Interest rate	-0.0046	-0.5039	-0.0121	-1.2715
DLOG (real wages & salaries per person)	0.5245	2.0528	0.7250	9.2729
DLOG (house prices)	0.1571	3.7423	0.0615	3.0216
DLOG (stock market value)	0.0361	3.0383	0.0104	1.8158
DLOG (oil prices, 4-qtr MA)	-0.0053	-0.6233	-0.0090	-1.2294

is possible because the model template is based on macroeconomic principles that most open economies adhere to. Such a structure also facilitates cross-country comparisons. And yet this model structure still allows nuances to be picked up specific to an individual country (see Table 11).

A quick glance at the consumption functions for the Netherlands and South Africa shows that they are almost alike in terms of explanatory variables but their coefficients differ vastly for the drivers of real consumption of goods and services. For instance, South African consumers have a higher propensity to consume out of their wages and salaries than Dutch consumers. On the other hand, Dutch consumers respond more strongly to the wealth effect—that is, they tend to increase consumption much more when house prices appreciate or when the stock market rises. South African consumers have a smaller wealth effect. Interest rates and oil prices hurt both countries' consumers, but South Africans are more susceptible because of higher inflation than in the Netherlands.

These inherent differences in economic structure also surface during scenario analysis. Without using overly complicated models, Moody's Analytics can deduce that the outcome of a 10% house price decline in both countries would be far more severe on consumption, and therefore GDP, in the Netherlands.

Customized specifications if needed. While the core structure of each model is the same, country-specific deviations in economic structure are built into the models whenever they are deemed to add value to

Table 12: Customizing Models: Spot the Difference

Dependent variable: DLOG (real exports of goods)

	Germany		China	
Sample (adjusted): 1999Q2-2012Q1	1999Q2- 2012Q1		2000Q4 -2010Q4	
Included observations: 49 after adjustments	49 after adjustments		41 after adjustments	
R-squared	0.7293		0.3340	
Adjusted R-squared	0.7234		0.3169	
Durbin-Watson stat	2.3229		1.6544	
Variable	Coefficient	t-Statistic	Coefficient	t-Statistic
Constant	0.0002	0.763	0.0144	2.113
DLOG (exchange rate: $/€)	-0.1302	-2.457		
DLOG (euro zone GDP, 2-qtr MA)	3.9799	12.758		
DLOG (exchange rate: yuan/$)			1.1096	2.599
DLOG (world GDP, 2-qtr MA)			4.5139	7.082

DLOG refers to the simple difference of a natural logarithm

the model's outcomes. Thus, for example, while it is accurate to have Chinese exports be driven by a global GDP measure, German exports are driven by the euro zone GDP (nearly 60% of German exports are destined for other EU countries), much like in the case of the U.K. (see Table 12).

Scenario driven. Besides providing plausible short- and long-term baseline forecasts, the models have also been designed to create alternative scenarios. To this end, once models are specified and their structure is diagnosed for accuracy, one of the tests is to apply hypothetical shocks such as global slowdowns, sovereign defaults, and stock market crashes to key aspects of the model. If the outcomes for components of the model such as trade, consumption or government spending are found lacking in any aspect, the model is retooled to better align outcomes to expectations based on historical patterns.

The impact of an oil price shock on gross domestic output of a country serves as a good example. Based on Moody's Analytics simulations, the treatment of oil prices is customized for each country depending on whether the country in question is an oil exporter or importer. A country exporting oil has equations linking the commodity sector to government revenue, augmenting sovereign wealth. An oil-importing country has oil prices appearing negatively in the key consumption equation.

Chart 6 shows the effect of a shock that raises oil prices by $150. Based on the specification, most oil-importing countries such as China and Japan experience a decrease in GDP four quarters after the shock is incorporated into the model. On the other hand, oil-exporting countries—Mexico, Norway and Russia—see their GDP rise because of this conducive shock.

Comparing alternative model specifications

In this section, the forecast accuracy of the country models is compared with

Chart 5: Core vs. Tailpipe Variables

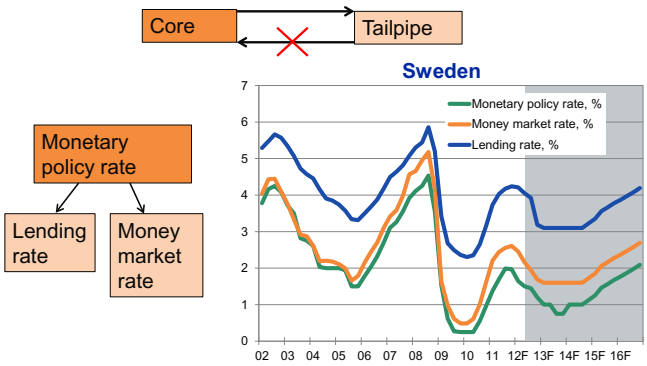


Chart 6: Scenario Driven

Consider a shock: Oil prices rise by $150 a barrel

Oil importers	Oil exporters
Oil prices rise => consumption falls => GDP falls	Oil prices rise => government revenue rises => GDP rises

	Importing countries			Exporting countries		
	CHINA	FRANCE	JAPAN	MEXICO	NORWAY	RUSSIA
% change in GDP (4 qtrs after shock)	-0.2286	-0.3801	-0.7085	0.9886	1.2778	2.4437

Table 13: In-Sample Forecast Comparison for France (Key Variables)

Forecast root mean squared error, % of Moody's forecast RMSE, 1999Q1-2011Q4

Variable	Description	Moody's Analytics	Random walk	Trend-stationary	Mixed	ARIMA
FWCL$Q	Household consumption expenditures	100.0	377.0	343.4	342.5	301.7
FWGL$Q	General government consumption	100.0	100.0	106.3	70.9	88.1
FWIFL$Q	Gross fixed capital formation	100.0	423.5	474.8	397.3	497.1
FWEXGSL$Q	Export of goods and services	100.0	206.6	71.1	76.9	188.8
FWIMGSL$Q	Import of goods and services	100.0	256.0	127.6	125.7	239.7
FWGDPL$Q	Gross domestic product	100.0	240.8	98.2	211.3	105.2
FWCPIQ	Consumer price index: All households, total	100.0	78.3	127.2	117.4	76.1
FWHPIQ	House price index: Existing houses & apartments, total	100.0	137.4	137.8	123.5	76.3
FWLBEQ	Labor force survey: Employed	100.0	111.8	86.8	81.6	117.1
FWLBRQ	Labor force survey: Unemployment rate	100.0	96.3	109.8	102.8	124.8
FWRGT10YQ	Interest rate: 10-yr government bond yield	100.0	164.3	97.6	100.0	100.0
FWSTOCKPQ	Stock market: CAC 40 index	100.0	192.0	198.6	128.0	125.3
FWYPDLQ	Gross disposable income	100.0	1144.4	413.6	408.6	732.1
FWYPEWSL$Q	Compensation of employees	100.0	1689.5	365.1	358.1	141.9
Mean		**100.0**	**372.7**	**197.0**	**188.9**	**208.1**

Source:

Sampling periods of regression for all models are 2000Q1-2011Q4.

Random walk models of log(variable) all have constant drifts.

ARIMA models of log(variable) are selected through minimizing the Schwarz information criterion.

Trend-stationary models are in the form of log(variable(t))=c+b*t, where t is the time index.

Mixed models are in the form of log(variable(t))=c+b1*t+b2*log(variable(t-1)).

four sets of alternative forecast model specifications. The first alternative is a set of random-walk-with-drift models. The second set assumes all log-transformed core variables following trend stationary processes. The third set includes simple mixed models with both time trends and lagged dependent variables.

The final set of models is composed of single-equation ARIMA models after the methods of Box and Jenkins. The log-transformed core variables are assumed to follow ARIMA(p,1,q) processes, with the autoregressive and moving average orders p and q selected individually for each variable through minimizing the Schwarz information criterion.[15]

An in-sample forecast comparison is presented in Table 13. All four sets of alternative models are based on regressions with a sampling period from the first quarter of 1999 to the fourth quarter of 2011, which is the regression period selected for the model for France. The forecast capacities of the four alternative models are then compared with the Moody's Analytics models in terms of the root mean squared error.[16] To facilitate comparison, the Moody's Analytics models' RMSE has been normalized to equal 100. For any of the alternative models to be deemed better than the Moody's Analytics models,

15 Schwarz information criterion is a statistical criterion for model selection. When estimating a model, one can always improve the fit by adding more variables. This may lead to "overfitting" in which irrelevant variables are added to fit the historical data movements due to random error. SIC handles the problem by introducing a penalty term for the number of variables in a model. When two models are compared based on SIC alone, the model with a lower SIC value is usually preferred. In our experiment, we loop through all reasonable ARIMA specifications for a variable and pick the model with the minimum SIC value.

16 The root mean square deviation or root mean square error is a frequently used measure of the differences between values predicted by a model or an estimator and the values. The RMSE is thus the distance, on average, of a data point from the fitted line, measured along a vertical line. The RMSE is directly interpretable in terms of measurement units, and so is a better measure of goodness of fit than a correlation coefficient.

Table 14: Out-of-Sample Forecast Comparison for France (Key Variables)

Forecast root mean squared error, % of Moody's forecast RMSE, 2009Q1-2011Q4

Variable	Description	Moody's	Random walk	Trend-stationary	Mixed	ARIMA
FWCL$Q	Household consumption expenditures	100.0	108.0	150.7	153.8	108.0
FWGL$Q	General government consumption	100.0	111.6	165.9	124.7	26.3
FWIFL$Q	Gross fixed capital formation	100.0	704.0	951.0	136.7	355.7
FWEXGSL$Q	Export of goods and services	100.0	200.6	150.1	160.5	124.4
FWIMGSL$Q	Import of goods and services	100.0	238.1	225.8	139.6	119.0
FWGDPL$Q	Gross domestic product	100.0	320.7	231.3	408.8	152.8
FWCPIQ	Consumer price index: All households, total	100.0	244.4	149.2	111.1	196.8
FWHPIQ	House price index: Existing houses & apartments, total	100.0	56.7	184.2	138.3	204.0
FWLBEQ	Labor force survey: Employed	100.0	283.0	470.0	475.0	1300.0
FWLBRQ	Labor force survey: Unemployment rate	100.0	265.2	224.8	221.1	161.5
FWRGT10YQ	Interest rate: 10-yr government bond yield	100.0	205.9	178.4	164.7	96.1
FWSTOCKPQ	Stock market: CAC 40 index	100.0	155.7	456.3	111.5	118.0
FWYPDLQ	Gross disposable income	100.0	832.9	945.5	960.8	704.2
FWYPEWSL$Q	Compensation of employees	100.0	105.1	143.6	130.8	107.7
Mean		**100.0**	**273.7**	**330.5**	**245.5**	**269.6**

Source:

Sampling periods of regression for all models are 1999Q1-2008Q4.

Random walk models of log(variable) all have constant drifts.

ARIMA models of log(variable) are selected through minimizing the Schwarz information criterion.

Trend-stationary models are in the form of log(variable(t))=c+b*t, where t is the time index.

Mixed models are in the form of log(variable(t))=c+b1*t+b2*log(variable(t-1)).

the RMSE of an alternative model must be below 100.

The forecasts from the Moody's Analytics fundamentals-based models performed better than all of the alternative models. On average, the random-walk models appear to be the worst among all five model types. On average, its forecast error is about 3.7 times that of the Moody's Analytics forecasts. This forecast comparison result suggests that the best forecasts for macroeconomic variables need not be the past values alone. Economic fundamentals do carry extra information that adds value to the forecast.

Mixed models performed better than ARIMA and trend stationary models. Yet on average, they still have an RMSE 88% greater than the Moody's Analytics forecasts.

Further, the Moody's Analytics models, on average, not only performed better than the potential alternatives, but they beat the alternative models in almost every one-to-one accuracy comparison.

A more rigorous comparison of the forecast capacities of various models includes out-of-sample tests. The performance of out-of-sample forecasts is similar to the actual task of forecasting. In this test, the coefficients obtained through historical regression are used to predict results in a time frame not covered by the model regression.

In an out-of-sample backcast comparison, the Moody's Analytics forecasts not only outperformed all the alternative models in terms of RMSE on average, but they once again performed better in most one-to-one forecast comparisons (see Table 14). All models tested are based on regressions over the sampling period from the first quarter of 1999 to the fourth quarter of 2008, and forecast accuracy is measured for the period from the first quarter of 2009 to the fourth quarter of 2011.

Conclusions

Many countries across the globe are going through times of macroeconomic uncertainty. Good forecasts based on

fundamentals-driven models can help guide policymaking investment decisions. In addition, through scenario analysis, these models can also help set up contingency plans for potential shocks.

Moody's Analytics has developed a set of global forecasts covering key macroeconomic variables (see Appendix for a list of variables). The forecasts are rooted in modern macroeconomic forecast literature and are based on a thorough understanding of the economic drivers affecting individual variables in each country.

The Moody's Analytics global country models are fundamental-based. Each equation in the forecast system is carefully selected from a group of candidate models, after comparisons based on the understanding of economic drivers, statistical properties of estimates, and backcast accuracies. As a result, models meet tests of accuracy while providing good economic intuition. They nearly always outperform competing candidate models constructed by Moody's Analytics in in-sample and out-of-sample accuracy tests.

The Moody's Analytics forecasts are updated on a monthly basis and provide a detailed macroeconomic outlook of all key variables that shape the most important economies in the world.

Appendix: Catalog of Variables

Note: .IGEO appended to a mnemonic indicates the country of the model

Variable type	Moody's Analytics mnemonic	Description
Exogenous	FPOP0014Q.IGEO	Population, ages 14 and under
	FPOP1564Q.IGEO	Population, ages 15 to 64
	FPOP65GQ.IGEO	Population, ages 65 and greater
	FPOPQ.IGEO	Population, total
	FTFXIEUZNQ.IUSA	Nominal exchange rate, $/€
	FCPIQ.IWRLD	Index: Consumer price, global
	FCPIQ.IEUZN	Index: Consumer price, euro zone
	FCPIQ.IUSA	Index: Consumer price, U.S.
	FCPIFICEBOIU.IUSA	Index: Brent crude oil, U.S.
	FGDPD$AQ.IWRLD	GDP, global
	FGDPL$Q.IEUZN	GDP, euro zone
	FRMPOLQ.IUSA	Interest rate: Central bank monetary policy rate, U.S.
	FRMPOLQ.IEUZN	Interest rate: Central bank monetary policy rate, euro zone
Endogenous		
Core	FRMPOLQ.IGEO	Monetary policy interest rate: Discount rate
	FRGT10YQ.IGEO	Interest rate: 10-yr government bond yield
	FSTOCKPQ.IGEO	Stock market: Country-specific stock index
	FTFXIUSAQ.IGEO	Trade: Exchange rate, local currency/dollar
	FGL$Q.IGEO	National accounts: Government consumption, local currency
	FCL$Q.IGEO	National accounts: Private consumption, local currency
	FIFL$Q.IGEO	National accounts: Gross fixed capital formation, local currency
	FIIL$Q.IGEO	National accounts: Changes in inventory, local currency
	FEXGSL$Q.IGEO	National accounts: Export of goods and services, local currency
	FIMGSL$Q.IGEO	National accounts: Import of goods and services, local currency
	FLBFQ.IGEO	Labor force survey: Labor force
	FLBRQ.IGEO	Labor force survey: Unemployment rate
	FCPIQ.IGEO	Index: Consumer price
	FPDIIMGSQ.IGEO	Implicit price deflator: Import of goods and services
	FYPEWSL$Q.IGEO	National accounts: Gross national income, local currency
	FGGREVTOTLQ.IGEO	Government finance: Revenue, local currency
	FGGEXPTOTLQ.IGEO	Government finance: Expenditure, local currency
	FHPIQ.IGEO	House price: Index or avg price

Appendix: Catalog of Variables, cont'd.

Note: .IGEO appended to a mnemonic indicates the country of the model

Variable type	Moody's Analytics mnemonic	Description
Tailpipe	FRMMQ.IGEO	Interest rate: Money market rate
	FRLENDQ.IGEO	Interest rate: Lending rate
	FM?LQ.IGEO	Money supply: M3 or M4, varies by country
	FPDIGQ.IGEO	Implicit price deflator: Government consumption, index
	FPDICQ.IGEO	Implicit price deflator: Private consumption, index
	FPDIIFQ.IGEO	Implicit price deflator: Gross fixed capital formation, index
	FPDIIQ.IGEO	Implicit price deflator: Gross capital formation, index
	FPDIEXGSQ.IGEO	Implicit price deflator: Export of goods and services, index
	FPDIGDPQ.IGEO	Implicit price deflator: Gross domestic product, index
	FPPPQ.IGEO	World development indicators: Purchasing power parity - PPP conversion factor to official exchange rate ratio
	FPPIQ.IGEO	Producer price index: Total, index
	FRTSALESL$Q.IGEO	Retail sales: Total
	FTABLQ.IGEO	Balance of payments: Current account balance, local currency
	FIPQ.IGEO	Industrial production: Total, index
	FGGDEBTLQ.IGEO	Government finance: Debt outstanding, local currency
	FGGINTPLQ.IGEO	Government finance: Interest payments, local currency
Identities		
Core	FWIL$Q_IGEO	National accounts: Gross capital formation, local currency
	FWGDPL$Q_IGEO	National accounts: Gross domestic product, local currency
	FWDDEMANDL$Q_IGEO	National accounts: Domestic demand, local currency
	FWGDPDISCL$Q_IGEO	National accounts: GDP discrepancy, local currency
	FWLBEQ_IGEO	Labor force survey: Total employment
	FWGGBBLQ_IGEO	Government finance: Budget balance, local currency
Tailpipe	FWTFXIEUZNQ_IGEO	Trade: Nominal exchange rate, local currency/€

Appendix: Catalog of Variables, cont'd.

Note: .IGEO appended to a mnemonic indicates the country of the model

Variable type	Moody's Analytics mnemonic	Description
	FWTFXIGBRQ_IGEO	Trade: Nominal exchange rate, local currency/£
	FWTFXIJPNQ_IGEO	Trade: Nominal exchange rate, local currency/¥
	FWGLQ_IGEO	National accounts: Government consumption, local currency, nominal
	FWCLQ_IGEO	National accounts: Private consumption, local currency, nominal
	FWIFLQ_IGEO	National accounts: Gross fixed capital formation, local currency, nominal
	FWILQ_IGEO	National accounts: Gross capital formation, local currency, nominal
	FWEXGSLQ_IGEO	National accounts: Export of goods and services, local currency, nominal
	FWIMGSLQ_IGEO	National accounts: Import of goods and services, local currency, nominal
	FWGDPLQ_IGEO	National accounts: Gross domestic product, local currency, nominal
	FWGD$Q_IGEO	National accounts: Government consumption, $
	FWCD$Q_IGEO	National accounts: Private consumption, $
	FWIFD$Q_IGEO	National accounts: Gross fixed capital formation, $
	FWID$Q_IGEO	National accounts: Gross capital formation, $
	FWEXGSD$Q_IGEO	National accounts: Export of goods and services, $
	FWIMGSD$Q_IGEO	National accounts: Import of goods and services, $
	FWGDPD$Q_IGEO	National accounts: Gross domestic product, $
	FWDDEMANDLQ_IGEO	National accounts: Domestic demand, local currency, nominal
	FWDDEMANDD$Q_IGEO	National accounts: Domestic demand, $
	FWDDEMANDDQ_IGEO	National accounts: Domestic demand, $, nominal
	FWNETEXGSL$Q_IGEO	National accounts: Net exports, local currency
	FWNETEXGSLQ_IGEO	National accounts: Net exports, local currency, nominal
	FWNETEXGSD$Q_IGEO	National accounts: Net exports, $
	FWNETEXGSDQ_IGEO	National accounts: Net exports, $, nominal
	FWGDQ_IGEO	National Accounts: Government consumption, $, nominal
	FWCDQ_IGEO	National accounts: Private consumption, $, nominal
	FWIFDQ_IGEO	National accounts: Gross fixed capital formation, $, nominal
	FWIDQ_IGEO	National accounts: Gross capital formation, $, nominal
	FWEXGSDQ_IGEO	National accounts: Export of goods and services, $, nominal
	FWIMGSDQ_IGEO	National accounts: Import of goods and services, $, nominal
	FWGDPDQ_IGEO	National accounts: Gross domestic product, $, nominal
	FWLBUQ_IGEO	Labor force survey: Total unemployed
	FWYPEWSLQ_IGEO	National accounts: Gross national income, local currency, nominal
	FWYPEWSD$Q_IGEO	National accounts: Gross national income, $
	FWYPEWSDQ_IGEO	National accounts: Gross national income, $, nominal
	FGDPPPP$Q.IGEO	National accounts: Gross domestic product
	FGDPPPPQ.IGEO	National accounts: Gross domestic product
	FTABDQ.IGEO	Balance of payments: Current account balance, $
	FEULBRQ.IGEO	Labor force survey: EUROSTAT unemployment rate
	FHCPIQ	Prices: Harmonized consumer price index, total, SA
	FYPDLQ.IGEO	Personal income: Total national net disposable income, local currency
	FHCPIQ	Prices: Harmonized Consumer Price Index, Total, SA
	FYPDLQ.IGEO	Personal Income: Total National Net Disposable Income, Local Currency

About the Author

Sunayana Mehra

Sunayana Mehra is an economist with Moody's Analytics. She is an expert in econometrics and works primarily on product development. As an international analyst, Sunayana played a key role in the development and production of the new Global Forecasts and Alternative Scenarios product, which required model building and scenario assessment for 49 countries. She has also worked on developing commodity price forecasts and industry analysis. She was instrumental in putting together new products for the housing group such as the RealtyTrac Foreclosure Forecast and the Leading House Price Indicator for the Housing Market Monitor. Sunayana holds a PhD in economics from the University of Houston, where she also taught before joining Moody's Analytics. She also holds a master's and an MPhil degree in international economics from Jawaharlal Nehru University in India.

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Economic & Consumer Credit Analytics

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

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