Using Economic Models

Avery B. Shenfeld
Senior Economist
CIBC Wood Gundy

Economic models come in various forms. But no matter the form, all models have potential problems. Investment professionals must be aware of the various types of models and the problems associated with them, so that when they look at research, they can better judge its validity.

We all get inundated with research—reports produced by brokerage firms, journal articles, etc.—and have grown used to being skeptical of whether or not we can get any payoff from it. I will provide some guidelines for looking at statistical research—information with all sorts of equations, charts, and features that appear very impressive. Armed with these guidelines, as investment professionals you should be able to look behind the pretty wrappings to test whether the research is something that you might actually put money behind or something that can go in the filing cabinet under your desk. I will also describe how we use models at CIBC Wood Gundy to look at particular sectors of the economy.

FORECASTING APPROACHES

Economic forecasting can be divided into five groups based on the differing methodologies:

- econometric, or structural, models,
- leading-indicator approaches,
- technical analysis,
- judgmental techniques, and
- mixed analysis.

Econometric models. Econometric models are generally large-scale structural models of the economy. These structural models are the most formal examples of modeling and often run to hundreds of equations. For example, the research from places such as DRI/McGraw-Hill is based on models with hundreds or even thousands of equations and thousands of individual variables, which is very costly to maintain. Most investment professionals would find it extremely difficult to duplicate that type of research effort.

A structural model usually takes a group of “exogenous” variables—variables for which the modeler has to make assumptions—and uses those variables to project other variables that the model solves for. So, typically, a structural model has an equation or a group of equations for each part of the economy—for the consumer sector, for the business sector, for housing demand, for government spending, and so on—and it adds all the equations together. The model creates a picture of the economy, which in turn influences other equations that give such things as interest rates.

In addition to these complex models, some very straightforward methods of econometric modeling are in use. For example, a basic regression analysis, in which a line is fitted to the data to try to ascertain the influence of one particular variable on another, can serve as a form of econometric modeling.

Leading-indicator approaches. In the leading-indicator approach, forecasters try to develop lists of variables that predict the variable of interest. The lists are not necessarily built into any formal statistical model but rather are used as signposts of upcoming changes in bond yields, equity prices, and so on. The government publishes some leading indexes, and individual researchers and consulting firms have devised some composite indexes to try to capture what they think are advance warning signals for economic trends.

Technical analysis. Technical analysis looks at chart points, Elliot waves, etc., to generate forecasts. This approach is quite common, so I will not delve into the details.

Judgmental techniques. The judgmental method of forecasting uses the investment professional’s judgment about economic trends by taking a hodgepodge of indicators and trying to build a story of what the economy is likely to do. From that story,
the movements of bond yields and stock prices, for example, are forecasted.

**Mixed analysis.** The mixed approach is essentially the approach that we use at Wood Gundy. Broadly speaking, we use a judgmental approach but supplement it with models to serve as a test of the story created by our judgmental approach. So, for example, we might use a model that looks at how long-bond yields should respond to changes in short-term interest rates and then use that model to check whether or not our story on long rates and short rates is broadly consistent with the data.

**WHY USE MODELS?**

Using models, either exclusively or as part of a forecasting effort, allows for the testing of hypotheses and ideas. Examples of what can be tested include determining how much low interest rates stimulate growth and whether wages can be used as a predictor of inflation. One advantage of using a model is that it puts hypotheses to a formal test instead of simply looking at the data and trying to see whether some trend exists.

Models are also helpful in estimating sensitivities. Researchers may be quite confident that one thing affects another—that inflation affects interest rates, for example—but they want to know by how much. How much, for example, would a 1 percentage point rise in the U.S. Consumer Price Index typically translate into 10-year bond yields? Statistical techniques can be used to try to isolate that effect.

Using models and statistical techniques also helps in developing internally consistent forecasts. For example, when researchers are using a judgmental approach, they may fail to see that something they are implying about income growth does not jibe with their assumptions on employment growth. One benefit of a big, formal model is it makes sure that everything adds up.

Models are also used for running simulations of complex scenarios. For example, a government economist may need to find out what happens if interest rates and government spending are both cut. Often, estimating the combined impact of good news and bad news is difficult. The U.S. growth rate may pick up, but inflation may stay flat. Statistical modeling lets a researcher try to balance the various influences.

Finally, sometimes models are used because variables have an underlying statistical process that has information in it. For example, something may have a tendency to revert back to its mean, and the researcher may be able to use that tendency to develop a better forecast.

**PROBLEMS IN THE USE OF MODELS**

The basic problem with all models is reliability. If a particular model suggests gold is going to $500 an ounce, investment professionals need to know whether they should believe the model and buy gold. If I am going to impart any message, it is that as investment professionals you should be critical readers of research. One has to look for what could be wrong before accepting the research as valid. I will talk here about a number of the things that can go wrong that would leave the research looking good but the underlying data are suspect—in effect, cases in which you cannot judge the book by the cover.

**Implausible Results**

One common problem arises from a model with a lot of variables that then attempts to isolate one of them. Although the model claims to have found that the one particular variable influences a second, other variables do not seem to be working correctly. Take an absurd illustration: The model is indicating that the higher inflation goes, the lower interest rates should go. The tendency should be to be skeptical about the rest of the research, because what that error is implying is that something is not working in this model; therefore, the model’s predictions might be quite unreliable.

**Statistical versus “Real World” Significance**

Another issue arises when researchers say they have found a statistically significant relationship, say between the price of gold and inflation. The key is to look at the statistical significance, which is the technical term for saying that the statistics indicate that the variable has an influence. But that significance has to be contrasted with the questions, “Does the variable matter in the real world? Does it have enough of an influence to matter?”

Let me give an example. A colleague of mine spent a great deal of effort attempting to develop a model to predict the monthly nonfarm payrolls report, because if he knew what nonfarm payrolls were going to be, he could certainly make a lot of money. The obvious variable that people look at to predict nonfarm payrolls is the initial claims for unemployment benefits. People also use a continuing claims variable that measures the number of people who are still receiving benefits after the initial claim.

So, my colleague built a model. He had lots of statistical work, and he came up with something that he thought looked good. In other words, all the statistics seemed to be pointing to a reasonable amount of explanatory power in predicting monthly nonfarm payrolls, and it looked like something usable.
Next, he conducted a test for real-world significance. He asked whether the model explained the data any better than a naive forecast of assuming that this month’s nonfarm payrolls was simply the average of the three preceding months’ nonfarm payrolls. The answer unfortunately was no, it did not. Sometimes a model can look good on the surface, have lots of statistical explanatory power, but still not be of any use because it does not beat a naive approach; the model just does not have what it takes to truly capture the underlying data.

**Errors in Underlying Data**

Variables that are subject to massive revisions create another problem when using models. Charts usually show that in the past, a certain variable appears to have been a good predictor of some other variable of interest, such as long-bond yields. The problem is, the chart shows the final revised data, not the data that would have been available at the time. You should be very careful about research that uses data that are subject to large revisions, such as the payrolls reports and Canadian merchandise trade surplus. You need to know if the predictive relationship holds for the initially released data as well as it does for the revised data.

**Assumptions**

Assumptions, assumptions, assumptions. That is what people always say the economists of the world make. No model predicts every variable, so every model has to have some starting points. Unfortunately, for the Canadian economy, one starting point often is what the U.S. economy is going to do, which is as tough to forecast as the Canadian economy. Modelers do not want a model that uses variables that are themselves as tough to forecast as the variable they are trying to forecast.

Let me give an example. When I was in consulting, I did some modeling for a group of luxury car companies that wanted me to forecast the demand for luxury cars in Canada. When I talked to them about what variables they thought influenced the demand, they all agreed that the stock market is an important variable. When the stock market is doing well, people go out and buy Forsches. The problem with that variable is the inability to predict the stock market. You have to be careful when the assumed variables are themselves as difficult to forecast as the variable you are trying to get out of the model.

**Structural Changes**

Another problem is with structural changes in the economy. All models assume that past relationships have some validity in predicting future relationships. In the case of economies that are changing rapidly, where fundamental structural changes are taking place, one does not know whether or not those past situations have much validity in predicting the future.

For example, some people argue that with heightened international competition and more layoffs and turnover in the economy now, the unemployment rate can go a lot lower than it has in the past without stimulating inflation. Well, that prediction cannot be tested because it is a new phenomenon. We do not have enough data on this post-transition economy, high-layoff world to determine whether or not wage inflation will take place.

Robert Lucas, a Nobel Prize winning economist, poked some holes into a lot of the work on economic modeling. His argument is essentially that the very fact that people can observe a change in policy influences their behavior in response to it. He argued that an economic model that, for example, tries to simulate what happens if interest rates are cut, is in theory wrong, because the model cannot account for the fact that individuals in the economy, having seen in the past how interest rates affected the economy, would then change their behavior in response to interest rate changes. People would be trying to run ahead of what the policymakers were doing.

To some extent, this theory sounds farfetched. It makes it sound as if individuals are running their own little economic models to determine what they are doing, but it is not that farfetched. Think about the fact that the world is filled with economic commentators who are watching closely what is going on and are providing insights into what is likely to happen. Lucas may be right. Using past responses to policies, for example, to assess how the economy will perform in the future may be fundamentally flawed.

**Simultaneity**

A common error that sometimes creeps into modeling is “simultaneity,” which is the technical term for trying to measure the influence of one variable on another when that second variable also influences the first one. This phenomenon can cause statistical models to entirely mess up relationships.

For example, suppose the researcher is looking at the Canadian dollar. The tendency is to think that the narrower the Canada–U.S. interest rate spread, the weaker the Canadian dollar. A less generous spread or even a negative spread at the short end should dissuade people from putting short-term assets into the Canadian dollar, which would tend to weaken the currency. Running a statistical estimate of that theory and looking at spreads would show absolutely nothing. In other words, the statistical
model would indicate that spreads do not influence the Canadian dollar at all, so the Bank of Canada could cut interest rates by another 300 basis points (bps), get them down to basically zero, and the Canadian dollar should not be affected.

That intuition is wrong because the strength of the Canadian dollar also influences interest rate spreads. In periods when the Canadian dollar was strengthening, the Bank of Canada might have chosen to take advantage of that situation by cutting Canada–U.S. interest rate spreads. Spreads influence the Canadian dollar; the Canadian dollar influences spreads. A more complicated model is needed to capture both of those relationships at once, which essentially gets into a model with a couple of equations. An equation is needed to explain the Canadian dollar as function of a number of factors, such as resource prices and interest rate spreads. A separate equation is also needed that explains the Canada–U.S. interest rate spread and allows the spread to be a function of a number of variables, including, of course, the Canadian dollar.

**Robustness**

Another problem with models, and unfortunately assessing this problem is often difficult, is what is called the lack of “robustness,” which comes down to a matter of trust. If someone gets a piece of research from Avery Shenfeld at Wood Gundy, that person does not know how many different versions of the model I tried until I got one that worked. That is, I could have tried all kinds of variables, attempted a logarithmic form of the equation, and so on until finally I got the statistics showing a model that fits the data and also showing the effect that I was trying to investigate.

For example, if I am trying to argue that gold is a predictor of inflation, I could vary the start date of the data until I find a period when my hypothesis works. If I start the series in the first quarter of 1971, this theory works. But if I start the series in the third quarter of 1971 or in 1982, this theory may not work at all. In doing research, those seemingly minor choices about how the model is constructed should not affect the basic results.

As the reader of research, you have to be very careful and skeptical if you think the modeler tried lots of things before coming up with the results, but understanding the modeling process is very difficult. What you should look for are odd choices in how the model is set up, such as the starting date for the analysis. Robustness is tough to assess when reading the research, so it is somewhat a matter of trust.

**Data Mining**

Robustness gets at the general issue of data mining—making multiple calculations with the data in order to get something that works. We have all heard arguments and seen papers that claim to have found profound statistical evidence with a tremendous explanatory power showing that years ending in a seven are good for the stock market. The question is, did these researchers test years ending in zero, one, two, and so on, finding only a relationship in years ending in a seven so that is what they chose to present? If so, the statistical tests are, in effect, cheating, because what the statistical tests indicate is a 90 percent confidence interval—the researchers are 90 percent sure that the relationship is not because of chance. In other words, what they are saying is a 1-in-10 chance exists that this relationship would have been found purely by chance. Well, if the researcher tries 10 such 1-in-10 chances, that person is likely to find a relationship. Those relationships, however, have no validity. That researcher has merely kept trying until lucking out, in effect, finding something totally unrelated to the data.

**Time-Series Data**

Time-series data sometimes have a number of problems. Unfortunately for economists and investment professionals, we cannot rerun the world and observe how the economy performs; we cannot rerun the 1980s and do something a little different. We have only this one set of data to work with, the data over time. Data over time present a number of problems for statisticians. For one, the data tend to violate many textbook assumptions on the purity of statistical tests.

A classic example of data problems occurs when variables have a trend to them. Most economic variables are trending up over time because the economy is growing, the population is growing, and so on. Variables that are trending over time often show relationships with each other. So, I could pick two variables that are trending up—say, the population of Japan and Canadian car sales. What I conclude from my statistical tests, if I want to predict Canadian car sales in the year 2000, is that I simply need to know the population of Japan. Well, that result cannot be right. What is wrong is that those variables have an underlying trend to them. A variety of statistical methods can be used to try to eliminate those spurious relationships between variables that have a trend, thus separating out the influences of trends and divergences from trends.

**Vector Autoregressive Equations**

Models called vector autoregressive equations, which have very little structure imposed on them, are
sometimes used. Vector autoregressive equations do not try to impose too much structure on the data in terms of which variables influence which other variables. Rather, they take some variables and assume that their historical values are related to some of the other variables’ historical values in the model. In the extreme case, this approach is like statistical work without theory.

**USING MODELS**

At Wood Gundy, models are an integral part of our work and our forecasts. One model that we use looks at the demand for Canadian commodities and tries to assess the influence of global industrial production on commodity prices. We also use a number of other variables that we think influence commodity prices. Because the prices are in U.S. dollars, we take a look at the value of the U.S. dollar against the G–10 index of other exchange rates. We then look at inflation, as measured by the U.S. Producer Price Index, as a predictor of gold prices. Finally, we use one of those complicated structural models—in this case something called an autoregressive moving-average process, which allows for trends and the tendency for commodity prices to overshoot and revert back to the trend. This approach seems to work reasonably well. When we ran it in February 1996, it indicated a weakening of base metal prices and a strengthening in energy prices. Many of the broad predictions that the model made seemed to pan out.

Another approach we take is what I referred to earlier as the mixed approach. That is, we look at a judgmental model and then test it to see if the data support the story that the judgmental model produced. For example, I often heard our foreign exchange traders say that they were surprised that the Canadian dollar did well because the U.S. dollar had weakened against the German mark. Many people in Canada believe that if the U.S. dollar weakens against international currencies, the Canadian dollar will weaken against the U.S. dollar. A test of this judgmental model revealed that no such relationship existed. Thus, sometimes statistical methods invalidate the old canards of forecasting.

Another approach we take is the leading-indicator approach. The Granger causality test attempts to answer a very simple question: “Do trends in one variable lead movements in another variable?” We used a Granger causality test to look at provincial bond spreads—for example, the spread between Ontario bonds and Canadian bonds in the Canadian market—to determine whether those spreads lead or lag the spread in the U.S. market for the same credits. We found that a leading relationship does exist in which the Canadian spreads are a little bit ahead of the U.S. spreads.

**CONCLUSION**

The bottom line on models is, do they tell us anything at all? I would argue that they do, but they are better at testing hypotheses than forecasting per se, because they do not seem to do any better than judgmental forecasts on average. Having said that, models do have some value in terms of simulating complex issues and testing to see whether one’s intuition is correct that a particular variable has in fact had an influence on another one. A problem with all of this analysis is, we can have the best economic forecasts and still be wrong on the markets. The problem that we often face as investment professionals and advisors is that, although we may have a model that perfectly predicts nonfarm payrolls, for example, deciding what the market has already assumed is often difficult. The ultimate problem with models is that sometimes translating what they indicate into good financial investments is difficult.