Futureskills Scotland

Uses and Abuses of Forecasting

Bridget Rosewell,
Volterra Consulting

Highlands & Islands ENTERPRISE

Scottish Enterprise

CONTENTS

FOREWORD

Bridget Rosewell is an acknowledged expert in the world of economic forecasting. Her expertise in the technical aspects is demonstrated in this paper by her detailed dissection of the forecasting process. More importantly, Bridget's experience as a senior economic adviser ensures that she can provide expert advice to policymakers on how to make best use of economic forecasts.

The briefing paper covers three main aspects of the forecasting process:

- **an examination and critique of the various methods of producing forecasts;**
- **a description of the inherent difficulties in economic forecasting; and**
- **advice to policymakers on how to make best use of forecasts.**

Bridget's paper recognises that we all need to plan for the future. We seek confirmation of future conditions to enable us to take appropriate actions now. In many cases, we seek a certainty in future conditions that only the unwise or unscrupulous would guarantee.

There are a number of conditions which assist in develop a model-based forecasting process:

- **'predictability' - the more uncertainty exists in any given system, the more difficult it is to predict;**
- **historical perspective - the greater our past knowledge, the greater our understanding of likely future conditions;**
- **understanding drivers - if we can isolate and understand the main drivers of any system, the better our forecast is likely to become;**
- **measurement issues - the more accurately we can measure the variables underpinning the forecast, the lower the scope for error; and**
- **model error - in general, the better our model fits the actual data, the lower the scope for forecast error.**

Model-based forecasts are useful. They lend an air of sophistication to the art of forecasting. In this paper, Bridget Rosewell rightly points out the role of expert judgement in adapting model outcomes.

Economic forecasts are useful to policymakers in terms of informing current decisions. Any policy has the potential to affect the outcomes of our forecasts. However, in some cases the policies adopted are implemented intentionally through a desire to confound the forecast, to prevent undesirable outcomes. Policymakers act to prevent the forecast conditions coming to pass. In such cases, the self-defeating prophecy inherent in the forecast makes assessing forecast performance very difficult.

Bridget's analysis provides a route for us to begin to bridge the gap between producers and users of economic forecasts in Scotland. A more detailed appreciation of the entire forecasting process from need through production to use can only be beneficial all round.

Futureskills Scotland welcomes this report. It provides analysis and advice from a recognised expert on how to develop an improved forward-looking analysis of the Scottish labour market. Such an approach would recognise the inherent difficulties in forecasting; it would also provide something which could be more easily used by Scottish policymakers.

Futureskills Scotland
March 2007

Note: the views expressed in this briefing paper are those of the author and are not necessarily those of Futureskills Scotland.

ABOUT THE AUTHOR

Bridget Rosewell is Chairman of Volterra Consulting and one of the most experienced economists working in business in the UK. She is also currently the Chief Economist to the Greater London Authority and advises the Treasury Select Committee on monetary policy. She has been engaged in forecasting the UK and other economies for over 20 years, from working for the CBI, through founding Business Strategies (now Experian Business Strategies) and now with Volterra.

Volterra has been founded by herself and Paul Ormerod to develop new techniques of economic analysis in a number of fields. They have pioneered new ways of undertaking risk assessments, transport appraisals and economic development studies as well as new forecasting tools.

SUMMARY

This report examines the different methods by which forecasts can be prepared, the risks to forecasting and how to interpret the results. It also examines the potential for preparing forecasts for employment in Scotland.

Forecasts are not just about how we expect the world to be but also inform how we might change it. It is important to understand the difference and the ability to form any views about what will or might or could happen.

Forecasts need not require statistical analysis of past data. The use of expert judgement is common in forecasting, both where no data exists and where it is judged that data may not tell the whole story. Both expert and group judgement can be shown to produce accurate and useful results in some circumstances.

However, most economic forecasts are based on statistical analysis of some form. First, an assessment of the accuracy of any data is needed, and particularly how consistent it is over time. Economic data is quite imperfect and measurement error may indeed be increasing as more variability in kinds of output or types of employment occur.

Second, not all data series can be forecast. If there is a lot of random noise in the series, it may be difficult to extract the movement which has some pattern. This applies whether or not it is clear what ought to drive movement in the series.

Understanding the drivers of a system may not help much in forecasting it. Many complex and non-linear systems can be quite simple to describe and give straightforward behaviour on average but cannot be predicted from day to day. Alternatively, short term predictability may collapse as time passes. Finally, even if the system has a straightforward relationship between its drivers and the variable of interest - for example output drives employment - this pushes the problem back to forecasting output and in turn the drivers of output and so on and so on.

Interpreting the results of any forecasting exercise means being aware of these limitations and how important they are.

Judging the performance of a forecast can be tricky if it is used as a guide to policy making. The purpose of the policy will be to adjust the existing parameters of the system, by providing more training for example, which will change the outcome in comparison with what was previously expected.

In an uncertain system, looking at ranges of potential outcomes can be helpful. The Bank of England does this in preparing its fan charts. This approach stresses that several possibilities are inherent in the existing data. This can be distinguished from scenarios in which a more detailed story of how policy makers react to particular shocks ought to be included.

Employment in Scotland is not measured with certainty - different measurement systems have produced different results. A merged series can be created, and does show an upward trend. However an examination of the rate of change shows great variability. This suggests that levels are fairly stable but change can go in either direction in any year.

It will require judgement to address the extent to which stable trends could be affected by new forms of structural change which are not already embedded in the system. Year to year changes will much more difficult to model at any level.

INTRODUCTION

The need and desire to know and to control the future are deep seated ones. By looking into the future we believe we will be better placed to take the right actions to guarantee our future success and indeed survival. Every day, newspapers and magazines publish forecasts of what individuals and groups can expect to happen today, this week or next week. Weather forecasts tell us whether we need an umbrella, while horoscopes tell us whether we will be lucky in love.

To understand what a forecast tells us and how it can be used requires an understanding of both the parallels and the differences between a weather forecast and a horoscope. This briefing looks at how forecasts are prepared and the methodologies that can be used. It uses these to illustrate how we can and how we should use forecasts.

One important element in this is to consider what is being forecast. If we forecast the weather, we are reasonably clear that we are looking at the future of a system which is outside our control (although even that is called into question by projects to create rain clouds). However, most forecasts in history have been made of human activities, from asking if I will win this battle to whether enough people will buy my product. On the basis of these forecasts, people act. Often they act in the hope of changing the outcome. Is there going to be a supply of skilled labour in this location in the future? In response the answer yes, my new investment absorbs the supply and changes the answer, falsifying the forecast as it does so.

This briefing also looks at the risks to creating a forecast, both to our ability to understand a given system and to the risk we will undermine this ability by our subsequent use of the analysis. In doing so, I also consider the difference between forecasting and scenarios, and between understanding and forecasting.

Finally I review the ability to provide reliable employment forecasts in Scotland and the risks to their accuracy in this case.

METHODS OF FORECASTING

Divination, Delphi and Expert Judgement

There are very few of us who have never thrown a die to decide an action. Heads or tails, you or me. Reading entrails, throwing sticks, examining tea leaves are all methods of trying to see into the future. They are still widely used, by Presidents of the USA as well as by primitive tribes.

At one level, some of us think of these methods as driven by chance, but at another they are in fact invoking expert judgement. The Delphic forecasting method is described for business use, for example in a guide to business forecasting from LloydsTSB, as using expert knowledge to take a view on the future. In the more esoteric branches of such judgements, a view may be taken on the influence of the stars, or other spiritual forces. There is usually an expert needed to interpret these forces. The original Delphic oracle was of course notorious for providing judgements whose interpretation was open to doubt. Such of course is still the case with experts!

Nonetheless, experts are consulted for their views on what is likely to happen, to a market as to a law case. Such methods are both respectable and researched. They appear in Handbooks on forecasting methods[1].

As well as consulting an expert, or an oracle, we can of course consult many such. The study of group forecasting goes back to the father of statistical analysis, Francis Galton. Towards the end of life he attended a country fair in which there was a competition to guess the weight of an ox. Being the man he was, he persuaded the organisers to give him all the entry tickets afterwards. He discovered, on analysis of these without the benefit of a spreadsheet programme, that the best predictor of the weight of the ox was the average of all estimates[2]. His insight has been documented on many subsequent occasions. The estimate of the 'crowd' may be better than the estimate of the expert.

This is the generally the case so long as the crowd members are independent and unbiased – quite often this is not true and group members may become influenced by a dominant member or subscribe to a particular theory. Whether you choose a particular expert or convene a group, an understanding of who the members are is crucial.

The modern application of this approach was developed in the USA by RAND, who used it to assist the military in thinking about technologies which would be useful to them. It is still most widely used in considering technological futures and guessing about applications. Programmes such as the Foresight programme, run by the Office of Science and Technology in the Department of Trade and Industry, uses these techniques.

They are most often used where there is no substitute for judgement because there is no relevant information from the past on which to base a statistical approach.

But the role of judgement should not be underestimated or swept under the carpet as we will see when considering apparently more scientific methods.

Statistics and Measurement

The adage of garbage in, garbage out is well known and too often ignored. Even before considering statistical model building, it is important to understand the limitations of the information you are working with.

There are several reasons why there may be limitations. First, there are errors in measurement. Economic output, for example, is a slippery concept. We may be able to measure the output of cars in any particular year, but even so comparing the number of cars produced this year with those produced last year poses problems of measurement when there are quality differences. This year's cars may all have air conditioning and ABS, which makes them better and more expensive, even though the actual number of cars has remained the same as last year, when only half the cars had this feature. So we may want to say that the value of the car industry has increased, in spite of no rise in the cars produced. If the problem is quite hard in the case of cars, where at least there is a physical object to measure, it is multiplied in the case of service sectors. Measuring the output of the accountancy or legal profession except by the numbers of accountants or lawyers employed is especially problematic.

[1] Principles of Forecasting: A Handbook for Researchers and Practitioners, J. Scott Armstrong, (Ed.), (2001),Boston: Kluwer Academic Publishers,

[2] I am indebted for this anecdote to James Surowiecki, **The Wisdom of Crowds: Why the Many Are Smarter Than the Few and How Collective Wisdom Shapes Business, Economies, Societies and Nations,** Random House, 2004

As for the output of the public sector, Professor Atkinson of Nuffield College Oxford led a year-long review of the issue, without being able to reach firm conclusions except more research would be required[3].

Measuring employment is by comparison much simpler. Even here, however, there are complications. We may find it relatively easy to count heads of those employed. But what about their hours? Do we want to correct for part time employment and if so what proportion of a full time employee does a part time one represent. The standard definition of part time is fewer than 30 hours a week. A full time employee may be working only 5 hours more. Many part time workers of course only work 10 hours, or term time hours or one of many other combinations.

These problems are magnified where there are fewer data points. Only a few employers and any change in a single employer's activity will have a large effect on the statistics without necessarily reflecting a more general change. And errors in measurement can distort the results much more in a small area than when there are many observations.

Some of this may be just nit picking, but if patterns change substantially over time then our time series may be distorted in important ways if we fail to take account of these changes.

And a time series is crucial to forecasting. Understanding the present cannot by itself lead to an understanding of the future. For this, knowledge of the past is also required, so that we see how the system has performed under different circumstances. To take an example, we know that rich people are able to save more than poor people. It ought therefore to follow that as we get richer over time, we will generally save more. However, this is not the case. The amount we save varies over the cycle but has not trended upwards at all.

As well as being able to measure the variables of interest, they also need to be more than random. Random variables, by their nature, cannot be forecast. Consider once again the die. If it is a fair die, repeated throws will generate equal occurrences of each face. But on each separate throw, there is an equal chance of any particular face and this is as good as forecast as it is possible to make. It is this combination of certainty and chance which is exploited by Tom Stoppard in **'Rosencrantz and Guildenstern are Dead'**. They flip coins continually, and the coin comes down on the same side each time. Each throw is independent, so each throw could come down the same side. But the laws of statistics say this will not happen.

Moreover, at least the die only has six faces. Most economic data has a much wider potential for variation and the capacity to exhibit greater randomness. An analogy might help to illuminate the issue. We might think of the problem as, say, attempting to decide whether a particular radio signal received contains genuine information (say, a piece of music) or is simply a combination of random squeals and hisses. Modern mathematical techniques can identify the proportion of the sequence which contains recognisable patterns, which can therefore be presumed to be genuine music (the "signal"), and the proportion which is simply interference (the "noise").

The existence of a relatively high degree of "signal" to "noise" is a necessary condition for reasonable forecasts of the relevant data series to be made. A series dominated by noise is very similar to a purely random series which, by definition, cannot be consistently forecast with any degree of accuracy. In the same way, a series which is dominated by noise is inherently difficult to model.

Economic data in general contains a high degree of noise, and hence contains very limited amounts of true information[4]. This is particularly the case when we consider growth rates of variables rather than their levels, and it is growth rates rather than levels which are usually the focus of interest. So, for example, the level of employment this year will be very similar to the level of employment last year, but what we are usually interested in is the growth between the two years.

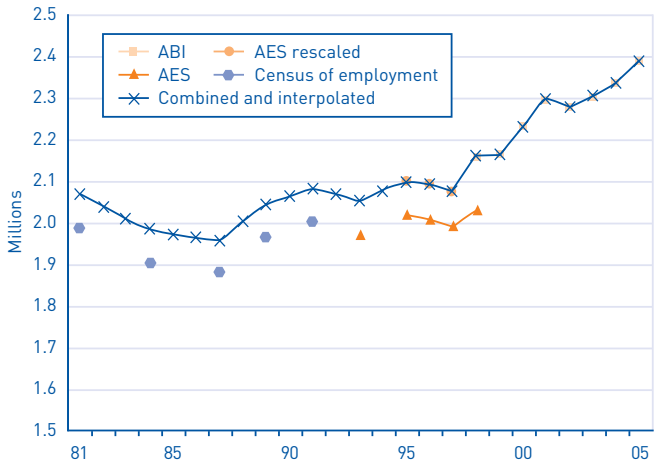
Curve Fitting

There is usually no substitute for drawing pictures. Consider the following two charts. One shows employment levels in Scotland, and the other the percentage change year on year. One looks as if there is an underlying pattern which we can identify and exploit. The other is a mess. If the interest is in a medium to long term trend, then the data suggest it can be unscrambled, although there are data difficulties in merging different data sets collected at different times. The Chart shows the actual data points as well as a series which merges these and adjusts for new data collection methods. These are calibrated to treat the more recent data as more correct, although this is itself an assumption.

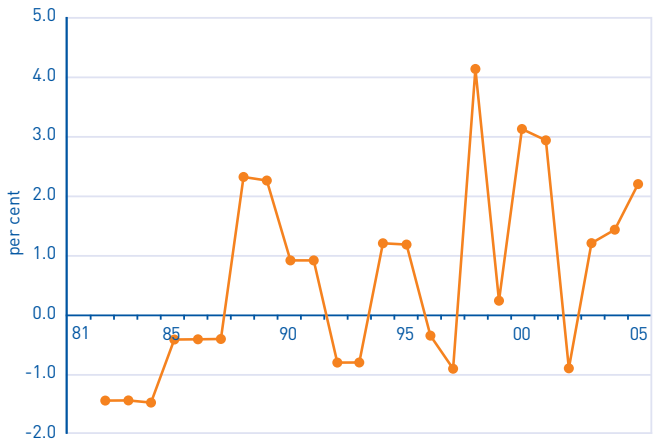
[3] Atkinson Review, Final Report, Measurement of Government Output and Productivity for the National Accounts, Palgrave, 2005

[4] An illustration of the application of the techniques which demonstrate this result is given in, for example, P.Ormerod and C.Mounfield 'Random Matrix Theory and the Failure of Macro-economic Forecasting', **Physica** A, vol. 280, 2000.

Total Scotland employee levels



Total Scotland employee growth



On a year to year basis the picture shows much more variability. It is hard to discern much of any kind of cyclical pattern, even though there are more than twenty years covered by the series.

The long term trend in employment can be thought of as the combination of a trend in output and in productivity. Faster growth in output with given productivity growth will generate more jobs. Faster productivity growth with given output growth will cut back on job growth. So long as secure trends exist in each area, a projection can be made.

This is the way in which we have thought about the projections over ten years or more for the London economy. If London's output grows at the same average rate as the UK, and its productivity growth remains on trend, we can infer employment growth. In practice, the data show a shift in trend over time and so the projection uses a mix of the current and the longer term trend, shifting to the longer term as the forecast horizon lengthens. The method was introduced in 2002, with data only available at that time up to 2000. Employment data for 2005 has just been released and over this five year period, the trend has been maintained, even though year to year actual outcomes have been both above and below it.

This method is essentially curve fitting. It looks at the history of the data and projects the trends which the data exhibits. In looking at longer term, or average performance it can be a good approach. However, it has some disadvantages. It tells you nothing about what is driving the trends and whether they are changing. Nor will it tell you anything about shorter term fluctuations - the year to year changes in the rate of growth.

Getting the story straight

Most people think of a model as a system which allows the analysis of causation. Consumer spending should be a function of income and wealth, and therefore changes in income and wealth drive the changes in consumer spending. Employment results from increases in output. These in turn result from increases in consumer spending, investment and so on. The model provides estimates of these relationships, and this in turn allows a forecast to be made.

In addition, the model allows us to tell a story about the forecast. This year, investment growth is expected to be particularly strong, and this will generate more employment growth is investment producing and using industries. Alternatively, if the consumer is especially buoyant, then retailing will do well, and so too will importer of consumer goods. I have been telling these stories for years, and they are quite plausible. Sometimes they are even right. Unfortunately, they do not derive from the model. It would be more accurate to say that they are imposed upon it. The model itself becomes little more than a check on the plausibility. If I make assertions about retail and about consumer spending, for example, will the model still add up?

Of course, this might be because I have failed to capture enough of what is going in the model. My model is actually a heuristic one operating in my head - an expert judgement system - rather than statistically based.

The role of judgement is in practice crucial to all published forecasts. Forecasters will make manual adjustments to the numbers which emerge from their model. These adjustments go under a variety of names such as 'intercept adjustments', 'constant adjustments' or 'residual fixing'. The Treasury goes even further and has two separate types, known prosaically as type 1 and type 2 adjustments. The leading academic econometrician and economic model builder David Hendry[5] has gone much further still, and claims to have identified several different reasons why the raw output of a model should be over-ridden, and the appropriate way in which to do so in each case.

It can be safely asserted that very few, if any, macro-economic forecasters use the pure, unadjusted output of their models when producing a forecast[6]. The output of the model is adjusted not just for the period between the time at which the forecast is carried out and when official data ends, but for the immediate future, covering the period **beyond** the start of the forecast. There is a small but, in this context, important literature which discusses the role of model adjustments in forecasting[7]. The evidence is clear that macro-economic forecasts carried out **with** judgemental adjustments to the output of the model, no matter how poor these might be, are in general more accurate than the use of the pure, unadjusted output of the model.

In other words, the practice of adjusting the raw output of a forecasting model has a perfectly respectable pedigree and is used extensively, not least within the Treasury. These adjustments are used both to refine the estimates of what has happened in the recent past and to incorporate judgement about what might happen in the immediate future.

In practice, therefore, actual economic forecasts are a mixture of an expert and a statistical approach.

Building a better model

It is useful to consider whether it would be possible to do better. A useful analogy here is with the weather. Weather systems are very complicated. A lot of different factors affect whether it will rain tomorrow. Underlying climate is one factor, but then winds, season, cloud formation, tide and so on all enter in. A model which can cope with all of these has to be very large and cope with many time scales and lags.

The advent of super computers has undoubtedly helped as have better measurement systems for weather conditions around the globe. Weather forecast accuracy has improved enormously, as data have become more accurate and more timely and computer simulations have become better able to cope with large amounts of information and interaction.

But they are certainly not perfect. In 2005/6 the Meteorological Office in the UK only had 85% accuracy for its prediction of the likelihood of rain on the next day in 11 cities last year.

So far, we have identified several reasons why accuracy might be curtailed. First, there are problems with measurement of the relevant variables. Weather men are always looking for better measures of the wind, temperature and so on at more places around the globe to get the models right.

Second, there is the inability to model. Too much randomness means no forecast is possible. Third, there is model error. This can take two forms. One is more straightforward than the other, though neither is easy to fix.

In general, a wide variety of techniques can be used to build models for employment projections, despite the shortage of observations. But conventional statistical theory implies that the shortage will affect the potential degree of accuracy of forecasts, no matter what technique is used. The potential forecasting error according to such theory depends upon three things:

- **how well the model fits the actual data. The better it fits, the lower is the range of potential forecast error**
- **how many observations there are. The more there are, the lower is the range of potential forecast error**
- **the values which the 'drivers' of the model take in the future. The further these are away from the values experienced in the period over which the model is estimated, the wider is the range of potential forecast error. And the smaller the number of actual observations, in general the more likely this is to be the case**

The most important sources of forecasting error do not, however, arise from the above, important though they may be. In calculating the formula for the potential range of prediction error around any model, classical statistical theory assumes that the model is 'the' correct representation of the data.

[5] MP Clements and DF Hendry, Macroeconomic forecasting and modelling', **Economic Journal**, 105, 1995

[6] Ray Fair in the US is the notable exception to this. Details of his model and forecasting record can be found at **http://fairmodel.econ.yale.edu/main2.htm**

[7] Perhaps the first article to draw attention to this is MJC Surrey and PA Ormerod 'Formal and informal aspects of forecasting with an econometric model', **National Institute Economic Review**, 81, 1977

In practice, the most important source of forecasting error comes under the heading of 'model error'. In other words, we can rarely if ever be sure, no matter how extensively we test the model, that we have 'the' correct model. We are not working with long, clean series of data from experiments in the natural sciences. We are working with data which is short and is certainly measured with error. The importance of model error is by no means restricted to economic forecasting models, but is considerably more general[8].

Such considerations are particularly relevant, for example, to climate change models. Here the aim is to forecast what the climate might be like as much as 200 years into the future. Such models experience all the difficulties which I have already outlined. First, there is insufficient data. Global climate data is not available on a consistent and accurate basis for more than 100 years into the past. Some would argue the period is shorter. To forecast 200 years on 100 years data is very risky.

Second, the models themselves are a poor fit to the data. Although the mechanisms by which carbon dioxide creates global warming are well known and produced by a simple physical mechanism which was identified in the 18th century, the actual path followed by carbon dioxide emissions and temperature change does not follow the predictions of these mechanisms. There has been too much warming when emissions were not changing and too little when they were rising sharply. Clearly there are other mechanisms which are also important but climate scientists are still struggling to build models, for example, of cloud formation. This is known to have a role in temperature change, but is hard to pin down.

Third, there is the scope for uncertainty and unpredictability. Weather forecasts more than 10 days out see a rapid fall off in accuracy. On the other hand average weather forecasts over a long period can be pretty good. This is the butterfly effect, perhaps rather misleadingly labelled 'chaos'. Chaos in model systems does not produce any old outcome. Usually, there is a fairly limited space of potential places that the system can achieve. What cannot be predicted is where in that space the system might be at any point in time. When first identified by Lorenz, he showed that tiny changes in the starting point of the model - the butterfly flapped its wings - the path of the system could diverge dramatically over time from its original path.

This is because non-linearities and feedbacks magnify the effects of this small change. Fortunately for economics, the signs of chaotic relationships are not strong in economic data. But mild non-linearities do appear to be present.

David Hendry of Nuffield College Oxford, probably the foremost academic time series econometrician in the UK, has looked at this. In both Clements and Hendry (1995) and Hendry (1996)[9] he argues that not only does there tend to be non-linearity in much economic data, but that any relationships which might be discovered may vary over time. For example the model which describes, say, the relationship between employment and output in one particular period may be different in another period.

A non-linear relationship between two variables means that the effect of a particular change in one of them on the other will depend on the value from which we start. So, for example, to take a very simple example, suppose a variable 'y' is exactly equal to the square of another variable 'x'. When x is equal to 1, y equals 1. When we increase x by 1 to be 2, y becomes 4, and when x is increased by s further 1 to 3, y becomes 9. So the effect of a change of 1 in the value of x changes the value of y by different amounts.

The extent of non-linearity must not be exaggerated, and it is usually fairly mild[10]. But if it exists, the task of identifying even an approximately correct model is made harder. Real-life examples are rarely as clear-cut as the illustrative example in the paragraph above.

[8] See, for example, C Chatfield, 'Model uncertainty, data mining and statistical inference', **Journal of the Royal Statistical Society A**, 158, 1995

[9] DF Hendry, 'Business cycle empirics', **Economic Journal**, 106, 1996

[10] See, for example, SM Potter, 'A nonlinear approach to US GDP', **Journal of Applied Econometrics**, 10, 1995 and GC Tiao and RS Tsay, 'Some advances in non-linear and adaptive modelling in time-series analysis', **Journal of Forecasting**, 13, 1994

SELF-FULFILLING AND SELF-DEFEATING FORECASTS

Systems in social science are not independent of the people who inhabit and analyse them. The main purpose of economic forecasts is to help make a decision. The Bank of England Monetary Policy Committee prepares forecasts of where it thinks the economy is headed. On the basis of this view it makes changes to interest rates in order to alter the future path from what it otherwise might be.

Success is measured in this case to the extent the outturn is other than the forecast had originally predicted. This complicates and undermines the ability to measure forecast performance. The usual way of considering whether the model is any good is to look back on how it predicted what happened after the event. But if the model's forecasts are being used to adapt behaviour then it becomes extremely difficult to test for model and forecast performance.

From a policy perspective this may not matter. For example, the forecast may suggest that demand will increase for people with computer skills. The policy response is to create more courses for these skills and to encourage individuals to acquire them. How is it possible to judge the success of this strategy? Even if the employment rate of those with the new skills rises, it may be for a number of reasons which have nothing to do with the accuracy of the forecast. Their computer skills are quite likely to be only part of their acquiring employment and may or may not be heavily used in the job.

Nonetheless the strategy may still be judged a success in increasing employability and the forecast itself has only a tangential relationship to this.

On the other side of the coin, a failure to respond may generate the market signals needed to encourage investment. Rising demand for computer skills pushes up wages if there are too few workers with such skills. This in itself encourages individuals to take up training and to try and enter this employment area. If the excess demand never develops, this looks like planning success, but may fail to attract enough of the right kind of individuals into the new area.

RISKS AND PREDICTABILITY

Much of the time, forecasts are uncertain. The Bank of England itself publishes a range of forecasts in the quarterly Inflation Report . The range attempts to capture 90 per cent of the possible outcomes, based on different assumptions about the drivers of the economy and also on uncertainties in the model.

What about the drivers

Many people fail to understand the difficulty of forecasting drivers. A model is built which explains the drivers of, for example, employment. Once employment is explained, then surely forecasting is easier. But this may well not be the case. Now we have to forecast the drivers as well.

To understand this, we need also to understand the difference between understanding and forecasting. To understand a relationship, we need to model the forces involved. Newton's laws of motion are derived from modelling the forces which apply to an object and solving for how they apply in the world. They can then be used to predict how any object will behave under these forces.

In this case, understanding allows for prediction. In the example of the die, or indeed of the behaviour of molecules in a gas, understanding does not allow for prediction. We can write equations for the forces which govern the behaviour of a die or the behaviour of the molecules which do not allow us to predict the position of the molecules of the next throw of the die. This is the case even though the equations perfectly model the behaviour of the system in question.

No amount of additional information will improve the position.

Even if, in principle, we can use our equation for forecasting, we are left looking for a mechanism which enables us to forecast the drivers. In the case of Newton's laws, the evidence is relatively easy to find. The economy presents greater difficulty.

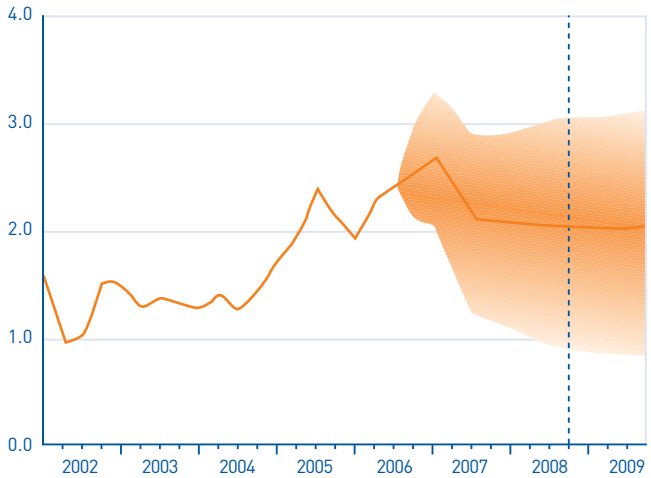
Many employment forecasting methodologies rely on predicting the performance of different industries. This in turn relies on the overall performance on the economy, and the relative performance of the different industries. The former is cyclical but each cycle is different. As a result the track record of the year to year forecast of the economy is weak. Quite often even the sign is wrong. Relative performance may be much more stable, and this can produce levels which do not change very much. But the rate of growth is much more volatile as we saw in the charts above. It is therefore hard to predict and can be quite wrong.

Reporting probabilities

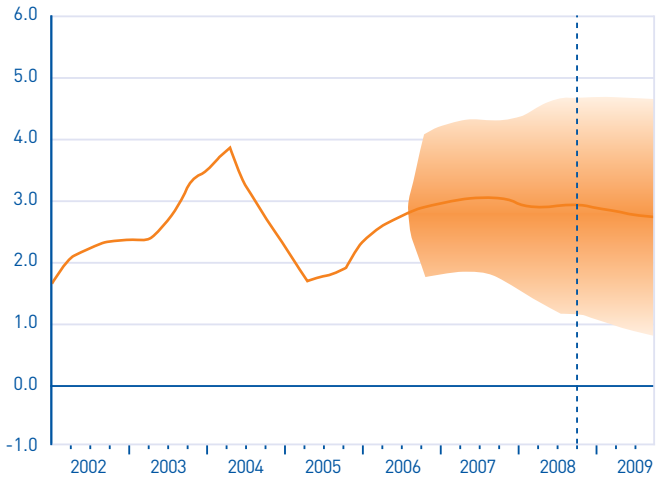
This is where probabilities come in. Most of us would prefer just one outcome, but it would be much more useful to know what the risk of being wrong is and how wide the outliers can be.

The charts below show the latest forecasts from the Bank of England. They show a central forecast but also how wide the Bank views the range of potential outcomes over the next two years. It provides useful additional information that none of their outcomes include a recession and none include inflation going higher than just over 3 per cent. This is actually quite a narrow range compared to previous experience, although the Bank's charts do not show a very long history.

Percentage increase in prices on a year earlier



Percentage increase in output on a year earlier



Scenarios

Probabilities are not the same as scenarios. In deriving a probability distribution, it is usual to run models many times to ensure that the space of potential outcomes is understood. Often these will be based on moving the starting point slightly as well as providing shocks to driver variables. In the macro economy, this might involve for example taking different views on the exchange rate, a variable which notoriously moves on a random path.

Scenarios on the other hand are more likely to be created by an expert judgement method, considering what kinds of outcomes create a coherent story. Policy reactions are often included. The Bank's probability charts are based on constant interest rates - a scenario would normally include a view on the likely reaction to different economic shocks in order to explore the consequences. From the point of view of Scottish employment policy, the knowledge that a particular shock to the exchange rate could cause economic difficulties is not very helpful if everyone agrees that moderating action would almost certainly be taken by the central bank.

CONCLUSION

Humans hanker for a certain world but at the same time want the freedom to make it better. This inherent contradiction is also embedded in our perspective on forecasting. The discussion in this paper shows that all forecasts will be wrong, at least to some extent.

As policy makers and economic agents, however, we have to take some kind of view of the future. There are many ways to create such a view, from personal introspection to canvassing the views of experts to statistical models. This paper concentrates on the strengths and weaknesses of quantitative forecasts, which are often (though not always) based on statistical approaches.

I have shown that taking a long term view of Scottish employment is feasible, but on a year to year basis it will be hard to be accurate. The ability to take a long term view however also implies that it is hard to change the underlying drivers of that employment prospect. Any such changes will be slow to take effect and to embed.

Just because policy may be a slow burn, this does not of course deny its efficacy. Maintaining policy under these circumstances does though requires determination and hard work.

If you require this publication in an alternative format and/or language please contact the Scottish Enterprise Helpline on 0845 607 8787 to discuss your needs.

Futureskills Scotland
Scottish Enterprise
150 Broomielaw
Atlantic Quay
Glasgow
G2 8LU
Tel: 0141 248 2700
Fax: 0141 221 3217

www.futureskillsscotland.org.uk
email: futureskillsscotland@scotent.co.uk

SE/1961/MAR07

Highlands & Islands ENTERPRISE

Scottish Enterprise