FORESIGHT

The International Journal of Applied Forecasting

THE ESSENTIAL READ FOR THE PRACTICING FORECASTER

CONTENTS

"Knowledge of truth is always more than theoretical and intellectual. It is the product of activity, as well as its cause. Scholarly reflection therefore must grow out of real problems, and not be the mere invention of professional scholars." *John Dewey, University of Vermont*

Editorial Statement

FORESIGHT, an official publication of the International Institute of Forecasters, seeks to advance the practice of forecasting. To this end, it will publish high-quality, peer-reviewed articles, and ensure that these are written in a concise, accessible style for forecasting analysts, managers, and students. Topics include:

- Design and Management of Forecasting Processes
- Forecast Model Building: The Practical Issues
- Forecasting Principles and Perspectives
- Integration of Forecasting Into Business Planning
- Forecasting Books, Software and Other Technology
- The World of Forecasting: Applications in Political, Climate and Media Forecasting
- Case Studies

Contributors of articles will include:

- Analysts and managers, examining the processes of forecasting within their organizations.
- Scholars, writing on the practical implications of their research.
- Consultants and vendors, reporting on forecasting challenges and potential solutions.

All invited and submitted papers will be subject to a blind editorial review. Accepted papers will be edited for clarity and style.

FORESIGHT welcomes advertising. Journal content, however, is the responsibility of, and solely at the discretion of, the editors. The journal will adhere to the highest standards of objectivity. Where an article describes the use of commercially available software or a licensed procedure, we will require the author to disclose any interest in the product, financial or otherwise. Moreover, we will discourage articles whose principal purpose is to promote a commercial product or service.

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FORESIGHT GOES QUARTERLY

Since its inception in 2005, *Foresight* has been published three times per year. With this, our 12th issue, we are pleased to announce that the journal becomes a quarterly. All memberships and subscriptions will be automatically extended to include four issues.

THE WINTER 2009 ISSUE

This issue features a section on improving communication and cooperation in the forecasting process. "The Forecasting Mantra," by ALEC FINNEY and MARTIN JOSEPH, is built on the authors' long experience in pharmaceutical forecasting, and proposes a "holistic" strategy for creating, communicating, and monitoring product forecasts. In "Sales Forecasting: Improving Cooperation Between the Demand People and the Supply People," TOM WALLACE and BOB STAHL address the major organizational gripes and myths impeding good forecasting practice and offer specific recommendations to resolve them.

No aspect of forecasting is attracting more interest now than Sales and Operations Planning (S&OP), and *Foresight* presents two reviews of *Sales and Operations Planning - Best Practices*, by John Dougherty and Christopher Gray. Our reviewers are Professor JOHN MELLO, an academic, and JOE MCCONNELL, a software developer, each with a special interest in S&OP. Both agree that the book makes a valuable contribution to the field.

As 2009 begins, the U.S. (and global) economy is in recession, yet few forecasters forewarned that recession was imminent. In "Predicting Recessions: A Regression (Probit) Model Approach," PETER SEPHTON discusses five key recession indicators, incorporating these into a model that forecasts the probability of recession up to 12 months in advance. The model tells us that the United States had fallen into recession by the third quarter of 2008 and likely will remain there into the third quarter of 2009.

KESTEN GREEN and I report the results of our second survey on forecast accuracy measurement, "Percentage-Error Metrics: What Denominator?" Should it be the Actual, the Forecast, or something else? We summarize the opinions of 60 respondents. Our first survey (Summer 2008) asked whether forecast error should be defined as Actual – Forecast or Forecast – Actual.

PAUL GOODWIN's Hot New Research column explores "New Evidence on the Value of Combining Forecasts."
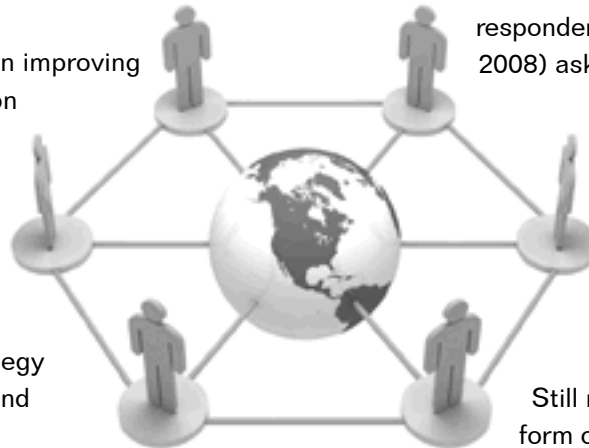
Still more proof comes in the form of the results from the U.S. presidential election. The Pollyvote forecasts, combining four types of election forecasts, came within a half-percentage point of the mark, outperforming most individual predictions. See "Combined Forecasts of the 2008 Election: The Pollyvote" by ANDREAS GRAEFE and the POLLYVOTE TEAM. Polly earns another cracker. Forecasts from 13 regression models described in the previous two issues of *Foresight* were wide ranging, but RANDALL JONES and ALFRED CUZÁN report in "Forecasting Performance of Regression Models in the 2008 Presidential Election" that a simple average of these forecasts came within 1 percentage point of President-elect Obama's share of the two-party vote.

This issue's Forecaster in the Field is CAROLYN ALLMON of ConAgra Foods, whose career spans the public and private sectors, and has addressed challenges ranging from tax revenue forecasting to forecasting systems' implementation.

As always, I welcome your feedback on *Foresight*.

Len Tashman

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UPCOMING

Special Feature on the Assessment of Forecastability
How to determine the forecastability of a time series (of a product or item), so that we have a basis for judging (a) the degree of accuracy we can strive for in forecasting the series and (b) our degree of success from applying a particular forecasting method to that series.

Forecast Process Improvement
- The Impact of Sales Forecast "Game Playing" on Supply Chains

Forecast Accuracy Measurement:
- Measuring Forecast Accuracy Improvement
- ABC-XYZ Analysis

Forecasting Principles and Methods
- Project Cost Forecasting
- Spare Parts Forecasting

- Columns on Forecasting Intelligence, Financial Forecasting, and Hot New Research
- Book and Software Reviews

The Forecasting Mantra: A Holistic Approach to Forecasting and Planning

ALEC FINNEY AND MARTIN JOSEPH
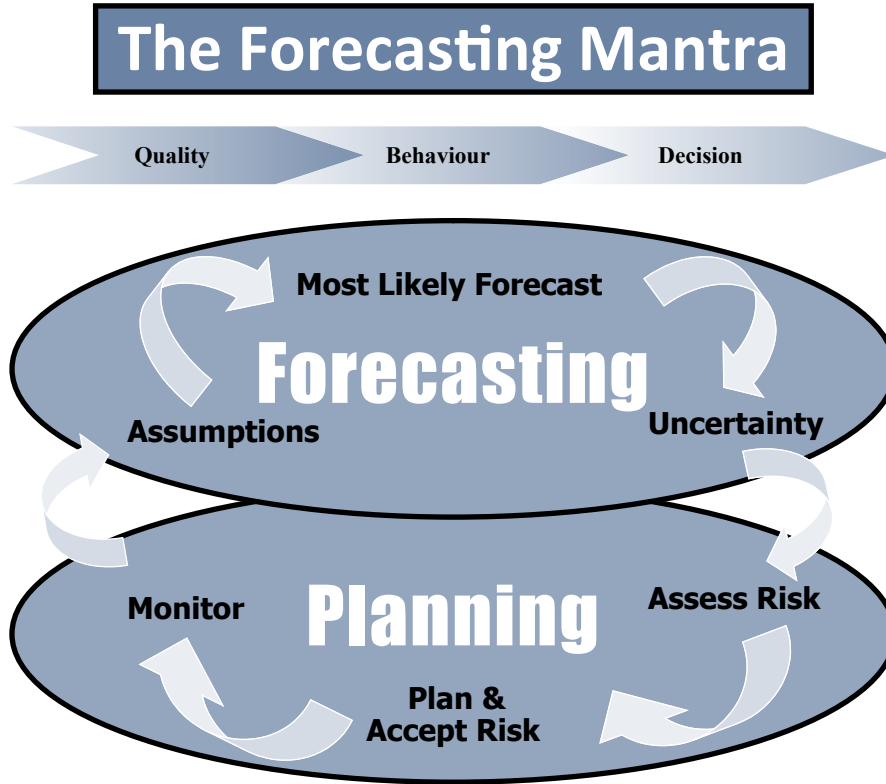
PREVIEW

Applying decades of experience in pharmaceutical forecasting, Alec Finney and Martin Joseph offer a template for steering the forecasting and planning process through organizational pitfalls to a successful outcome. Some lessons were learned the hard way; but aren't these lessons the most convincing?

INTRODUCTION

The Forecasting Mantra describes a holistic view of business forecasting which, coupled with mature behaviors, enables the delivery of high-quality forecasts and leads to improvements in target setting, risk management, and investment decisions, all of which improve bottom-line performance.

THE INEVITABILITY OF POLITICAL BIAS

In a letter to the French historian Jean-Baptiste Leroy in 1789, Benjamin Franklin wrote that, in this world, nothing can be said to be certain except death and taxes. The same sense of inevitability is applicable to political influences in forecasting. We contend that, with discipline and by following a logical flow of activities, organizations can avoid many of the inefficiencies caused by political bias.

Do these quotations sound familiar?

"This is the sales number we need next year."

"We used our new and expensive forecasting model/software for this forecast and this is the output."

"Fine, but we need 20% more sales to meet our business target."

"I want to see a single-number forecast reconciled with the budget and supply-chain forecasts."

"That's two months in a row we've been behind the phased budget. What are you going to do about it?"

"I didn't agree with that forecasting assumption to start with!"

"How do you get from those assumptions to these numbers? Tell me in a way I can understand…."

"How confident are you in that forecast – what risks do we face?"

These statements arise from neglect in stakeholder management, lack of understanding of the distinctions between forecasts and plans, poor communication of how the forecaster's assumptions link to the outputs, and the inability to provide context for the forecasts rather than presenting rows of numbers.

The business consequences are damaging: bad investment decisions, failure to manage risk and expectations, and excess inventory costs. But that's not all. The working environment becomes distrustful and inefficient. We lose confidence in our forecasts. We recycle decisions and overcomplicate business processes. Most importantly, we undervalue and demoralize our forecasters.

KEY POINTS

- The critical start point in any business forecasting and planning process is gaining agreement on the assumptions that will drive the forecasts. We recommend that assumptions be kept to a minimum and that all stakeholders sign off on them.

- Stakeholders need to be given answers to three basic questions:

  a. What is the most likely forecast based on the agreed-upon assumptions?
  b. How confident are we in this forecast? What is the likely range of possible outcomes?
  c. What other futures should we be made aware of – relating to changes in one or two key assumptions?

- Use a storyboard to present your forecasts to the organization. The best medium for the storyboard is the written word with a small number of embedded pictures.

- One of the most important tenets of the Mantra is that forecasts and plans need to be distinguishable. We stress the principle that the business plans for each functional process can and should operate using different numbers.

- Monitor outcomes against evidence of changes to the assumptions that drive the forecast – not just against numerical targets.

Alec Finney is Principal Consultant at Rivershill Consultancy Ltd. He was formerly Strategic Forecasting Manager in Global Marketing at AstraZeneca and previously Forecasting Manager at AstraZeneca's UK affiliate. In these roles he worked across functional boundaries to ensure the production of high-quality, actionable forecasting to help drive business processes, set targets and manage risk. He is now a regular speaker at international forecasting conferences and on the advisory board for eyeforpharma. Outside forecasting, he follows his beloved Liverpool soccer team and enjoys writing and searching out art deco antiques.

Martin Joseph is Managing Director of Rivershill Consultancy Ltd., based in the UK, specialising in business forecasting, planning and decision making. He was formerly Head of Information Management and Forecasting at AstraZeneca, in which role he was responsible for the global forecasting business processes and systems. Martin is a regular speaker at conferences on forecasting and supply chain planning, an Associate of Nine-TZ Healthcare Ventures, and a member of the Advisory Boards for the Institute of Business Forecasting and eyeforpharma.

> It's important to understand that assumptions are the input to the forecast, not the output. To state that "a market share of 30% will be reached 4 years after launch" is not an assumption, but a hope or aspiration.

With process discipline, however, these costly inefficiencies are not inevitable; most can be avoided. What follows is a framework (the Mantra) for efficient business forecasting and planning which, if embedded in business processes, will improve forecast accuracy, provide a consistent view of risk, and give better overall business control.

ASSUMPTIONS ARE THE KEY

One truism of creating high-quality forecasts is that a forecast can only be as good as the assumptions upon which it is based.

The critical start point in any business forecasting and planning process is to achieve agreement regarding the assumptions that will drive the forecasts. We recommend that assumptions be kept to a minimum. Forecasters and forecast users should resist the temptation to introduce factors which are not forecastable or that have minimal effect on the scale or accuracy of the output.

There are no fixed rules for classifying assumptions, but consider the following:

What is history telling us? Do we have a clear demand pattern that can be extrapolated into the future? The assumption is that the future could be very much like the past – but look out for key events that could affect this outcome.

How much better than the competitors are we now, and how will this change? It's important to think of how competitors will react to our new initiatives; they won't simply lie down.

Will we get the resources to successfully exploit our advantages? All too often, strategic planners believe they have a winner, but the affiliates aren't keen to commit resources.

What future events will have to be anticipated? The golden rule here is that they have to be big events. Many forecasts drown in their attempts to incorporate effects of future events. Consequently, as the impact of many effects is overplayed, transparency can be lost.

Assumption proliferation also can occur if the forecaster tries to respond to all the questions asked by business managers. The temptation to meet all such requests leads to overly complex forecast models and overly enthusiastic "what if" analyses.

Can the price be sustained? What are the likely pressures on price? Are there opportunities to be exploited – or are we working in an essentially price-inelastic market?

It's important to understand that assumptions are the input to the forecast, not the output. To state that "a market share of 30% will be reached 4 years after launch" is not an assumption, but a hope or aspiration. The aim of the forecasting process is to transform qualitative assumptions into quantitative outputs. Beware of outputs masquerading as assumptions.

Assumptions must also be consistent. For example, it is not plausible to assume a significant price premium for a me-too product.

And finally, all stakeholders must sign off on the assumptions. Under these circumstances, with professional facilitation and guidance, a great proportion of the bias, both political and systematic, can

be identified and removed. The purpose at this stage is to identify those assumptions which drive the forecast, influence the uncertainty, or help quantify the risk. This buy-in is essential to avoid constant reforecasting.

Having agreed upon the assumptions and business purpose, we now need to build a quality forecast.

CREATING A HIGH-QUALITY FORECAST SOME HARD-LEARNED LESSONS

The area of forecasting that receives the most attention is the creation of the forecast. We now have many forecasting packages to implement models, ranging from simple extrapolation techniques to sophisticated multivariate models. An examination of developments in this area is not the focus of this paper, but there are some notable fundamentals:

While different forecasting challenges require the use of different forecasting models, the chosen model should be as simple as possible. For short-term forecasts (the horizon will depend on the market sector), it may be a matter of agreeing that the future will be like the past, in terms of trend and volatility. Here an extrapolative forecasting method should provide an acceptable forecast. It is surprising how often this is the case.

For new-product forecasting, our experience in the pharmaceutical sector has told us that modelling should focus on just the three key drivers of market share – time to market, differential advantage, and relative *share of voice*, which is the amount of "noise" we are making in the market place. More than this only complicates the forecasts and gives the false message that the forecast can answer every conceivable "what if" question.

In some cases, good forecasts may require robust evidence of causal relationships. Let's take the example of differential advantage driving market

share. In the pharma world the attributes of a drug can be defined as *efficacy*, *safety*, *ease of use*, and *price*. For forecasting, a comprehensive regression analysis on historical data is necessary to establish the relative strength of these attributes as drivers of market share.

Similarly, a well known soup maker has produced a forecast model based on the lowest temperature recorded in any 24 hours at key cities in the UK. This simple, negative correlation worked well for them.

Simple logic is all that is required to structure a forecasting model. This point is not about modelling per se but about the logic that is used to establish the available market for a product and determine how that product is perceived by the consumer. It is usually in new-product forecasting that these logical frameworks tend to get much too complicated as the forecasters try to incorporate logic that closely mimics customer decision making.

Unnecessary complexity brings on difficulties in validation and additional maintenance and updating expenses, especially when third-party suppliers are commissioned to create the model.

We believe a simple three-step structure is better. The first step is to estimate the potential market, which determines the size of the opportunity or market-share ceiling for all the players in that market. The second and usually most difficult step is to model the market share that is expected for the product being forecasted and to determine whether the entrant will significantly expand the existing market. The third step breaks this market share into units (SKUs) and dollars.

PRESENTING THE FORECAST
The Most Likely Forecast
The concept of a "most likely forecast" (MLF) is the key to successful business planning. The MLF provides

the reference point against which other forecasts, scenarios (more about these later), and budget and supply plans can be compared. It is the touchstone for the development of functional business plans that, in turn, are used to set targets and manage risks.

The MLF is the most likely outcome derived from the forecast model built upon the most likely set of assumptions. The MLF is a single forecast which can be thought of as a 50:50 bet, where actual outcomes are equally likely to be above or below it.

But the MLF should not be considered the end point for the forecaster. With excellent assumptions and robust, evidence-based models transforming those assumptions into a numerical output, what more do our decision makers need? Well, the forecaster has to provide some context for the MLF.

Forecast Error vs. Uncertainty

We live in an imperfect, uncertain world. Driving business decisions with a one-line forecast – even with the bias squeezed out of it, and backed by the best set of assumptions – is a risky business. Before describing how the Mantra helps us deal with an uncertain world – a few definitions.

Corporations routinely confuse forecast error with uncertainty and risk. Even with perfect inputs – data and assumptions – the very best forecasting model will be in error due to the inherent variability in the data. The more volatile the data, the less forecastable the item.

Add in the inevitable uncertainty around the assumptions, and you can see why people always say, "A forecast is either wrong or lucky!" Uncertainty is the cause of business risk. The nature of this risk is different for decision making in different business processes. Businesses either have to knowingly accept inherent uncertainty or try to cope with it. With the

> Unnecessary complexity brings on difficulties in validation and additional maintenance and updating expenses, especially when third-party suppliers are commissioned to create the model.

latter, invariably, additional investment is necessary. Nearly all contingency plans carry a price tag!

So once we have created the MLF, we need to provide decision makers with an idea of the degree of error we can anticipate. The magnitude of uncertainty will be different for different forecasts. For one, it is a lot easier to forecast demand than ex-factory sales.

The Ansoff Product-Market Growth Matrix (Ansoff, 1957) of Figure 1 helps us to ponder uncertainty. Clearly, there is greater uncertainty when forecasting new products and when forecasting into new markets as opposed to existing markets. The uncertainty in a three-month forecast for an in-line brand with a stable

Figure 1. Igor Ansoff's Product-Market Growth Matrix
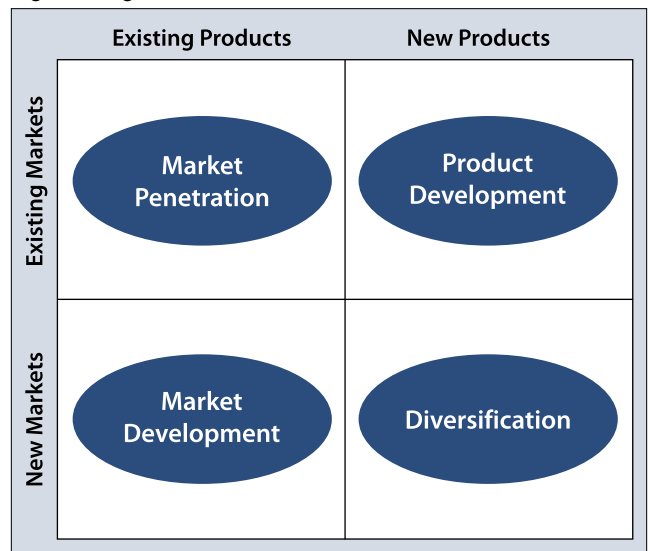
trend will be much smaller than for a 10-year forecast for a new product in a new market.

There are many ways to measure degrees of uncertainty. We can use judgments based on market intelligence, Monte Carlo simulations, out-of-sample evaluations, formal probabilistic approaches, and more. Whichever approach is used, the goal is to provide a "confidence interval" around the MLF.

A confidence (or prediction) interval would say, for example, that while the MLF is the best "one-line" forecast we have, we believe that 80% of all possible outcomes (based on our assumptions) will be within a certain distance of the MLF. So now we have a range or interval forecast, and not just a single-point MLF.

Alternative Scenarios

What other information does the decision maker need? Well, the MLF and the confidence interval are based on our best set of assumptions. What we need to do now is look back at these assumptions and pick out several that are critical to the forecast output that could – if they are wrong – create a radically different future.

We may have assumed an early arrival to market. So what would be the effect of coming in later, after our competitors have established themselves in the market? We may have assumed a competitor arriving after us with a differential advantage. What would be the benefit to us if they entered the market only as a me-too? By changing one of these key assumptions, we create a significant alternate future – scenarios that can be used to put the MLF into context.

To this point, we have answered these questions:

- What is the most likely forecast, based on the agreed-upon assumptions?
- How confident are we in this forecast? What is the likely range of possible outcomes?
- How sensitive are the forecasts to changes in key assumptions?

Figure 2 assembles the three factors.

Here's an example from the world of finance showing how context brings forecasts to life.

Bulletin from the Bank of England (June 2008): "We believe that, on balance, interest rates will be 6.35% at the end of 2008." **(MLF)**

"This assumes that the effect of subprime defaults has largely been squeezed out of the banking system and that the price of oil has peaked. By taking these inherent uncertainties into account, we are confident of outcomes between 6.0% and 6.7%." **(Confidence Interval around MLF)**

"However – although not in our view likely – if the political situation in the Middle East deteriorates further

Figure 2. MLF, Confidence Interval, and Scenarios
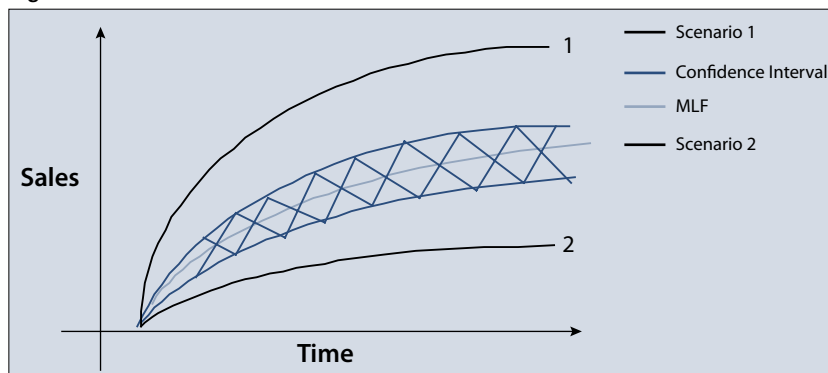
– leading to a significant reduction in oil production and distribution to Western economies – interest rates could dip as low as 3% in an effort to reduce the risk of out-and-out recession." **(Scenario Analysis)**

A word of caution here – many managers are not aware of the limitations of the sensitivity of forecasts to changes in assumptions. For example, forecasters are frequently charged with the task of informing business managers about the effect of changes to the marketing mix, level of representative promotion, or advertising. However, forecasting models may not be sufficiently sensitive to predict the effect of small changes to these variables, in which case, to avoid disappointment and frustration, decision makers should be made aware of this limitation.

The Storyboard

The forecaster now has a set of documents, analyses, and outputs; signed-off assumptions; and a forecast model or models with a set of scenarios. But frequently the model and scenarios are developed in Excel. Big mistake! Excel is not a tool that can be used with any degree of assurance in relating the "essence" of the forecast. A 50-deck PowerPoint presentation is not usually the answer either. What is needed is a *forecasting storyboard*. The best medium is Word with a small number of embedded pictures.

The storyboard is built on simple sentences. Here's a very simple storyboard for a short-term, in-line product forecast:

There is a strong historical trend for this product and no indication from commercial intelligence that the trend is about to change. Competitive activity is stable and again we have no indication that this will change. The growth we are experiencing is primarily a switch from our competitors – although there is some evidence we are growing the market with new customers.

The MLF is therefore a simple extrapolation using the last 12 months' data. The sensitivity analysis is around the possibility of further increases in market share. The only downside scenario would emerge if we significantly reduced our marketing and promotional spend.

Of course the narrative should be accompanied by a small number of pictures showing share history, estimated growth, and the impact of significant events. The important point is that the storyboard is about *words with supporting pictures*.

Nothing is said about Box Jenkins, regressions, MAPEs or dynamically stable systems, just a description of what the forecast represents. Of course, for a new product in a new market, there would be many other factors to consider – but the above gives the essential storyboard.

What we have been dealing with and expressing up until now is uncertainty around the forecast. The next step is for the business to decide on the degree of risk it is willing to accept.

ACCEPTING RISK AND DEVELOPING BUSINESS PLANS

Now we move into the *behaviors* space of the Mantra. Even if the forecasts are delivered in a logical, coherent storyboard, the forecaster's job is not done. The business still has to make decisions, based both on the forecaster's story and on the business context.

Concentrating on the forecaster's results, it is possible to take Figure 2 and present it another way, linking forecasts and plans (Figure 3).

Figure 3 shows forecast uncertainty from another angle: the cumulative probability of different outcomes. By definition, the MLF is associated with a 50% probability, so 50% on the vertical axis aligns with the

Figure 3. Linking Forecasts and Plans
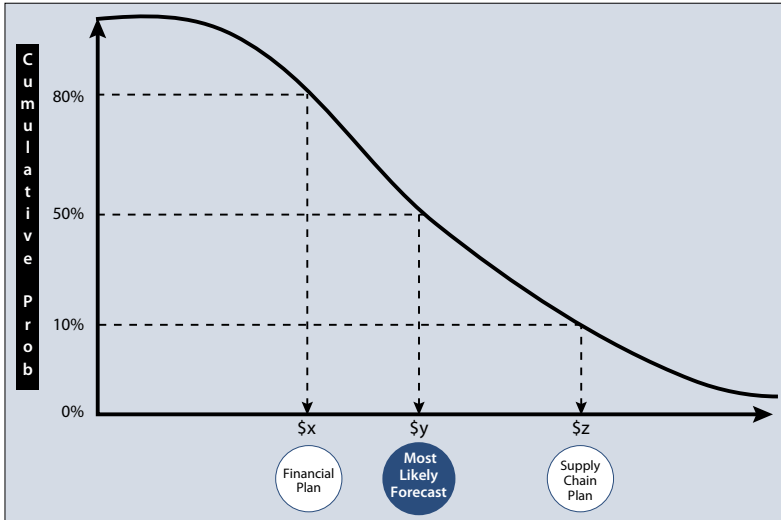
MLF of $y. However, there is a higher probability of achieving a smaller outcome of $x, and this smaller value might be used in financial plans to manage key stakeholder expectations.

Now consider the lower end of the scale – where there is a smaller chance of reaching sales of $z. Which forecast would the Supply Chain Director use in his manufacturing and distribution plans when, for example, launching a new product? Adopting the MLF would be a high-risk strategy, with a 50% chance of being under resourced.

A transparent trade-off between stock and capacity is facilitated by visibility of the MLF, the associated uncertainty, and guidance on assumptions used.

One of the most important tenets of the Mantra is that forecasts and plans need to be distinguishable. If a financial plan has to balance achievability with ambition, and a supply-chain plan has to balance risk with cost, how can they possibly be reconciled? They are independent in their objectives but common in terms of their specific relationship with the MLF.

While we do not intend to go into detail about how financial, marketing, or supply-chain functions can

manage their respective risks, we want to stress the principle that the business plans for each functional process can and should operate using different numbers. Derived from the MLF and its confidence interval, the numbers can coexist transparently across any organization.

For example, consider setting the annual budget. No matter how efficient, the budget process is often politically biased, and the final numbers frequently bear no resemblance to the current forecast (unless the budget is replayed as a forecast – an all-too-common problem!). Budget numbers are frequently used for target setting and rewarding performance, the root cause of bias in many instances.

By the end of the budget cycle, the forecasts used to create the budget will be at least one year old, and the current MLF may be substantially different. Some companies manage their business by reporting monthly deviations from budget or by comparisons with the same period in the previous year. We do not believe this helps guide the path for action. Rather than controlling the business on the basis of deviations from budget or comparisons with the same period in the previous year, we recommend displaying a *rolling MLF* in which the forecasts, plans, and budgets are updated through the forecasting cycle as new sales data come in.

Monitoring Assumptions: Well, That Was a Surprise!
Organizations require a sensitive intelligence system where early warning signals are used to prompt action. While actual sales outcome can provide some of those signals, assumptions also require monitoring.

We have also experienced the situation – many times – where the forecasting team (guardians of the MLF), the finance group (guardians of the budget), and the marketing people (guardians of the sales target) have

confused senior managers by delivering conflicting reports on business performance, accuracy, and risk. Here again it is important to use the MLF as the cornerstone of these reports. The other comparisons are important and show where value has been added to the MLF – and how well the respective business targets are being met.

We once observed a forecasting team reporting forecast error of 2% and finance reporting forecast error of 10%. The first was against the MLF and the second was against the budget. These two numbers are now shown on the same management report – and stimulate objective discussion on how the "target gap" can be bridged.

Were the assumptions right, but the forecast model erred? We recommend a mix of monitoring tools which pick up signals in demand patterns (absolute, trend, volatility, etc.) and those which constantly check the key assumptions for future validity. Of course it is necessary to have intelligence on the emergence of factors that were not included in the set of original assumptions.

SUMMARY

Let us go back to the questions posed at the beginning of this paper and see how the Mantra helps make sense of them.

"This is the sales number we need next year."

"We used our new and expensive forecasting model/ software for this forecast and this is the output."

"Fine, but we need 20% more sales to meet our business targets." (Understand the difference between forecasts and plans.)

"I want to see a single-number forecast reconciled with the budget and supply-chain forecasts." (Different plans meet different business purposes and cannot be reconciled.)

"That's two months in a row we've been behind the phased budget. What are you going to do about it?" (Monitor against assumptions – not just the numbers.)

"I didn't agree with that forecasting assumption to start with!" (Taking people along with you on the forecasting journey is vital.)

"How do you get from those assumptions to these numbers? Tell me in a way I can understand…." (Tell me the story of this forecast – the thinking behind the numbers.)

"How confident are you in that forecast – what risks do we face?" (Give me the MLF, confidence intervals, and scenarios.)

There is a virtuous circle of forecast quality and good decision making.

The Mantra, derived from our many years of experience, is our framework for producing a quality forecast (storyboard, assumptions, MLF, uncertainty). It is critical to distinguish between a quality forecast and the plans which such a forecast drives. And it is necessary to monitor the forecasts and the assumptions on which they were based.

REFERENCE

Ansoff, I. (1957). Strategies for diversification, *Harvard Business Review*, 35, Issue 5, 113-124.

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Sales Forecasting: Improving Cooperation Between the Demand People and the Supply People

TOM WALLACE AND BOB STAHL

PREVIEW

In this selection from their book *Sales Forecasting: A New Approach*, Tom Wallace and Bob Stahl identify some all-too-common beliefs ("gripes and myths") that can impede cooperation and consensus building in an organization's forecasting process. Here they prescribe some remedies for bettering the working relationships between demand folks and supply folks, thus enhancing the effectiveness of the forecasting process.

INTRODUCTION

A number of years ago, at a public seminar about managing demand and supply, a Marketing VP introduced himself: "Hi. I'm Joe Smith, VP of Marketing with Ajax Widgets."

The seminar leader said, "I'm not familiar with the widget business. Who's your competition?"

The VP of Marketing said, "Operations!"

Of course, it's a funny reply, but sadly it expresses the kind of situation that all too often defines the relationship between the demand and supply sides of a business.

Why are these relationships so adversarial? Why do these people hassle and complain about each other instead of devoting their time and mental energies to serving the customers? Well, there are a lot of reasons: functional silo organizations, misaligned performance measurements, left-brain vs. right-brain personalities, unenlightened leadership that pits one group against another, and – oh, yes – not doing the forecasting job well. This includes lack of accountability, poor forecasting processes, and unclear objectives.
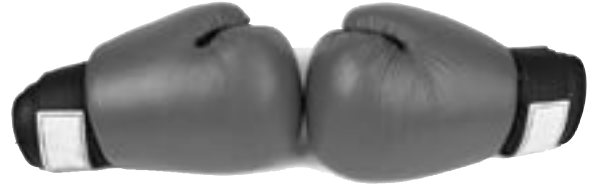
On top of all this, today there are two other very important factors that exacerbate the forecasting problems:

- Extensive broadening of demands from customers and users, contributing to end-item proliferation, and
- Longer and more variable lead times from outsourced manufacturing.

This article takes aim at some very common "gripes and myths" about the forecasting practice. By dispelling them, you should begin to see how to do the job of forecasting far differently than in the past. This can enable a "new approach" that will make things better on the forecasting front and hopefully create a mutually supportive – versus an adversarial – relationship between the demand folks (sales and marketing) and the supply folks (operations and purchasing).

Tom Wallace is a writer and educator specializing in Sales and Operations Planning. A Distinguished Fellow of Ohio State's Center for Operational Excellence, he has taught S&OP in North America and internationally: Australia, Belgium, China, France, Great Britain, and New Zealand. Tom has written twelve books, including *Sales & Operations Planning: The Executive's Guide*.

Bob Stahl has spent the last thirty-plus years as a practitioner and coach developing leading-edge processes for manufacturing, logistics, and supply-chain management. As an S&OP expert, he has worked with many of the world's leading corporations. Bob has coauthored six books with Tom Wallace, including *Sales & Operations Planning – The How-To Handbook*.

Let's get things started with . . .

#1 – You can't forecast this business.

Every company that makes and sells products is doing sales forecasting, either formally or by default. The challenge is to do it well . . . better than the competition.

You not only <u>can</u> forecast any business, you <u>must</u> for a number of reasons. If the sales and marketing people don't do it, people in purchasing, manufacturing, and finance will be forced to do it. This is because information about the future is vital for anticipating material and capacity needs required to satisfy customers, as well as projecting financial plans for which the company's leadership will be held accountable.

If forecasting is being done by default in purchasing, manufacturing, and finance, there are a number of problems:

- There are likely to be many forecasts that don't agree.
- People will be working to different plans, causing lack of teamwork.
- People who are not close to the marketplace are doing forecasting.
- Confusion, mistrust, and crisis will almost certainly ensue.

That brings us to the question, **what** must be forecast? The answer is two things – *volume* and *mix*. Volume is the big picture, focusing broadly on the market direction from which aggregate and strategic decisions can be seen and made. Mix is the customer-centric picture with much detail. A couple of definitions:

Volume Forecast: A forecast for groups of product that are similar in the way customers and/or markets view their use. These volume forecasts are used for rough-cut capacity planning at the plants and at suppliers, and

KEY POINTS

There are some very common gripes and myths about forecasting practice. By dispelling them, you'll see how to do the forecasting job better and perhaps far differently than you have in the past.

Gripes/Myths –

#1: You can't forecast this business.

#2: Forecasting is not in my job description; my job is to sell product.

#3: It's impossible to make any sense out of this forecasting stuff.

#4: An accurate forecast would solve all our problems.

#5: We need more detail in our forecast.

#6: Forecasting is a waste of time around here; nobody ever reads the forecasts.

#7: We know the forecast is going to be wrong, so why bother forecasting?

#8: In Operations, we're victims of Marketing's lousy forecasts. And there's nothing we can do.

for financial projections and analysis 18 to 24 months into the future. Rough-cut planning is done by using simplifying ratios about mix (the detail). These volume forecasts are grounded in extrinsic as well as intrinsic data and provide leading indicators of what's to come in the aggregate or big picture. They do not have full granular detail.

Mix Forecast: A forecast by individual product that is frequently customer driven. Sometimes called the detailed forecast, it is used for short-term scheduling of plants and suppliers and may also be required for certain unique long-lead-time purchased items.

These two forecasts are separate and distinct, involving very different procedures or practices. They must, however, be reconciled or integrated in the short term.

One has a total-market focus (volume) and the other has a customer-specific focus (mix).

The next question is: **Who** should forecast?

#2 – Forecasting's not in my job description; my job is to sell product.

One of our favorite statements is that nothing can happen until you sell something, but nothing does happen until you ship it. This statement gets at the fact that there are two parts of being successful in business – selling something and then planning and shipping it. Selling it without shipping it on time is not the goal. In order to do both parts successfully, the boundary between sales/marketing and operations must be blurred with regard to the forecasting practice.

The reason so many sales and marketing people are reluctant to assume responsibility for forecasting is that they're being asked – by operations, purchasing, and finance – to do something that they can't do and that makes no sense: they are being asked to forecast by end item for the full planning horizon. Think about the typical annual budgeting practice for many companies. With today's product proliferation and extended lead times, this method makes less sense than ever. The good news, alluded to in the last section, is you don't have to do it that way any more. There is a "new approach." Stay tuned; we'll get to **how** shortly.

When done properly, sales/marketing people will own the sales forecast (volume and mix); they are the ones who know the markets and customers best. We believe that this accountability is part of what makes a company's forecasting process work well.

Right now, some of you sales/marketing folks might be thinking: "Okay, I guess forecasting is necessary, and I can't argue with the idea that it's our job. But how are we going to do a good job of it when everybody agrees that the forecast won't be accurate?" We haven't talked, and will not talk, about an "accurate" forecast.

Keep reading.

#3 – It's impossible to make any sense out of this forecasting stuff.

Before we talk about *accuracy*, let's talk about *process*. We've learned from Total Quality Management (TQM) that processes can be improved and that's almost always a good thing to do. The reason: *better processes yield better results*. And, we hasten to add, better forecasting processes yield better forecasts, a point emphasized by Stephan Kolassa in his paper on benchmarking in Issue 11 of *Foresight (pp. 6-14)*.

As with all processes, forecasting has inputs, a conversion phase, and an output. The inputs to the forecasting process are:

Extrinsic Inputs	**Intrinsic Inputs**
Current customers	New products
New customers	Pricing
Competition	Promotions
Economic outlook	Bids
Other	Management Directives
	Intra-company demand
	History
	Miscellaneous

From these inputs, a company must craft a well-defined and disciplined process to project a volume forecast in families that is reasoned and reasonable. Specifically, this process defines:

- Who will do what by when;
- What the data inputs are; and
- What the data outputs will be.

Being reasoned and reasonable means that it makes sense based on past history, the current situation, and the changes expected in the future. As this aggregated volume forecast moves toward the *Planning Time Fence* (the point where actual scheduling takes place and specific detail is needed), the volume forecast needs to be converted to a detailed forecast. In other words, the mix forecast comes from the volume forecast – not the other way around.

Now it's time to talk about *forecast accuracy*.

> **#4 – If we could just get an accurate forecast, it would solve all our problems.**

There's no question that better accuracy in our forecasts is a desirable goal, but the way to get there is not by harping about forecast accuracy as an arbitrary measurement. It's a turnoff to the people who have to do the forecasting. Our position is this: the best way to increase forecast accuracy is to work on the process, focusing on reducing variability in the traditional Total Quality Management (TQM) sense. This may sound like semantics, but it's really not – it's a behavioral issue.

We've learned that processes have inherent variation, and because forecasting is a process there will be some variability. This means that some degree of forecast error is inevitable. There are companies that disregard this factor and push their sales/marketing people to make forecasts with a predetermined level of accuracy. We've seen this approach result in counterproductive behavior. Examples range from people switching off (refusing to forecast because it's a no-win deal and they're tired of getting beaten up) to forecasting too frequently (updating the forecast every few days based on the last few days' orders). Quality guru W. Edwards Deming referred to this as "tampering" – being given incentive to do the wrong thing and thus doing it. Neither of these kinds of behavior is helpful.

As you might guess at this point, we highly recommend the use of the tools from the TQM tool chest. They include run charts, control charts, Pareto charts, cause-and-effect analysis, and other tools to help manage the forecasting process. One last word on accuracy: a biased forecast is one that is consistently over or under. A biased forecast is almost always caused by factors outside the forecasting process. It frequently revolves around how people are evaluated and/or compensated. Biased forecasts are the worst kind of forecast error; strive for zero bias.

> **#5 – We need more detail in our forecast.**

Remember the days when all companies conducted an annual business-planning chore of forecasting the future in highly granular detail: by SKU (end-item), by customer, and by location? It tied everybody up for a month or two. Remember what we used to do with this forecast? We carefully calculated, with a great perception of precision, the material, capacity, and financial consequences for the next year.

As time marched on, what did the operations, purchasing, and financial people do with those projections? The typical answer – very little. They either second guessed these forecasts or ignored them. The reason? Even if they were initially accurate (and that's unlikely) they became less accurate over time, with no viable means to keep them current as things indeed changed.

If operations and/or finance continue to require the sales/marketing people to provide a fully detailed forecast over the entire planning horizon, it will drive this vital part of the team (sales/marketing) away from the table.

There is a principle here: if you forecast far into the future (a year or more), with a high degree of detail, accuracy will be at its worst! As we said earlier, there are two forecasts that are needed: volume (families) and mix (detail). The good news is that the detailed forecast is only needed for the *scheduling* horizon – for most companies this is less than six months, maybe less than three.

Without full detail beyond that, how do you make resource (capacity and suppliers) and financial projections for the balance of the horizon? The answer is by using simplifying ratios about the details of mix for the critical resources (inside and outside), and about financial projections. These ratios are determined by mining the detailed data of the past to find reliable simplifying ratios. Judgment about the future is then applied to make the projections reasoned and reasonable, driven by the family (volume) forecast. To ensure visibility and control over these simplifying ratios, you must maintain a classic TQM control chart showing the variability of the past and present, upper and lower control limits, and outliers.

If operations and/or finance continue to require the sales/marketing people to provide a fully detailed forecast over the entire planning horizon, it will drive this vital part of the team (sales/marketing) away from the table. This is because you'd be asking for something that cannot be done with any degree of reliability and update. Fortunately this practice is no longer necessary with today's best practices.

> #6 – Forecasting is a waste of time around here. Nobody ever reads the forecasts.

To better deal with this gripe/myth, let's examine the total use of forecasting for a typical business. The table below describes the varied uses for the forecast:

So the forecast feeds the planning functions for finance, sales-force staffing and activities, production capacity, supplier capacity and commitment, and is often a direct input into the master schedule.

If each of these departments has different forecasts for each of these different reasons, you can be sure they will never agree. This begs the question – how do you develop a single forecasting process that pulls all of this together so that you have one forecast with many views? Not to have one forecast with many views will surely result in a forecasting process that is collectively a waste of time.

The answer lies with leadership – that is, top management's willingness to lead an effective Executive S&OP process. If a company is unable or unwilling to put together a highly defined and disciplined Executive S&OP process, it is unlikely that the rest of the necessary activities will be done or tied together into a "one-number" system.

What is an effective Executive S&OP process? It is a set of monthly steps that updates the Annual Business Plan as things change. It culminates in a hands-on top

Use	**Unit of Measure**	**Forecast Horizon**
Financial planning	Dollars	Current & future fiscal years
Sales planning	Units/dollars	Weeks, months, quarters
Capacity planning	Units/hours	Months, quarters, years
Advanced procurement	Units	Weeks, months, quarters
Master scheduling	Units	Weeks, months

management meeting that makes decisions by:

- Balancing demand and supply at the volume level in both units and dollars.
- Tying operational plans to financial plans: one set of numbers.
- Reconciling volume and mix inside the Planning Time Fence.
- Acting as the forum for setting (or resetting) relevant strategy, policy, and risk assessment.

A vice president/general manager of a major business unit at Procter & Gamble said, "Our entire business team – marketing, sales, product supply, finance, R&D – is working more effectively now that we've stopped defending different volume estimates all month. We can pull together with a singe-number forecast that has everyone's full support." They no longer think, we might hasten to add, that forecasting is a waste of time.

> **#7 – We know the forecast is going to be wrong, so why bother forecasting?**

When we focus on observing variability as an alternative to harping on forecast accuracy, the whole issue takes on a new perspective.

When we think in terms of variability and its causes, not only does the forecasting process get better – as with any process – but we can separate the part of the forecast where high variability is unavoidable and come up with alternative solutions:

1. Buffer variability with
   - finished goods inventory
   - component inventory and finish to order (some call this "postponement")
   - manufacturing flexibility
   - promised lead time

2. Make some products to order with full-planning lead time

When we take the focus off accuracy and understand the intrinsic variability of a forecast, it's a different ball game. We stop blaming the marketing/sales force for lousy forecasts and start looking for ways to deal more effectively with intrinsic variability in intelligent ways. The forecasts will never be accurate across the board. Where they are not, we must look for alternatives.

One other point on the forecast being "wrong" – it's why this process must be reviewed and updated on a monthly basis. Things are changing – the earlier we recognize that the forecast is wrong, the better off we will be. We never want to blame the marketing/sales people for changing the forecast. We do, however, want to understand the reason for the change. Each month the marketing/sales people will be smarter about the future, and we never want to make them apologize for that or, worse, punish them for it.

> **#8 – In Operations, we're victims of marketing's lousy forecasts, and there's nothing we can do.**

A friend of ours once said, "The forecast should always be 100 percent accurate . . . if the lead time is zero." This is of course true – and impossible. But it's where operations folks can become participants instead of victims.

Companies can make great strides in their ability to service customers by applying three fundamental points to improve their forecasting processes:

1. Forecast less, not more.
2. Emphasize teamwork, not formulas.
3. Focus on process improvement, not forecast accuracy.

How do you forecast less? Operations folks provide two important parts to this objective. They can:

- Shorten lead times for the building of products where variability is high;
- Develop simplifying ratios so that rough-cut resource requirements and financial projections can be made from family forecasts, outside the Planning Time Fence.

Cooperative discussion about forecast variability begins, but does not end, with the planning part of the Executive S&OP planning process. Here is where policy, strategy, and risk issues are explored and decided upon. This in turn aligns human energy toward common actions to support common goals. Through controlled, cooperative discussion teamwork evolves – at both the executive and the doer levels. Putting the emphasis not on formulas but on teamwork across departmental boundaries is what brings about meaningful and useful forecasts.

Three fundamental points
to improve the forecasting
process:
- Forecast less, not more.
- Emphasize teamwork, not formulas.
- Focus on process improvement, not forecast accuracy.

CONCLUSION

We considered calling this article "Lean Forecasting." If you think about it, that might properly describe what we've talked about: doing more with less by getting rid of non-value-adding activities.

We'd like to conclude by quoting an executive from a company who followed this approach and created a transformational change in the way the business was run. He focused on the "less is more" theme, saying that they gained:

- More clarity on the current business condition,
- Less crunching of massive amounts of ultimately useless data,

- More understanding of where they want the business to be,
- Less confusion about where the company is and where it is going,

- More agreement on how they will get the business to where they want it to be,
- Less confusion surrounding business initiatives

- More accountability for the results, and
- Less waste of human and financial resources.

Simpler and Better! Either one of these in today's business environment would seem to be worth the effort. Getting both is even better, don't you think?

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"Sales & Operations Planning – Best Practices:
Lessons Learned From Worldwide Companies"
by John Dougherty and Christopher Gray

REVIEWED BY JOHN MELLO

PREVIEW

Given the virtual explosion of interest in Sales & Operations Planning, Foresight commissioned book reviews from both an academic and a software developer. We begin with Professor John Mello's review, followed by that of Joe McConnell, principal of McConnell Chase Software Works.

S ales and Operations Planning (S&OP) is a cooperative, cross-functional effort within a business that uses market intelligence and key metrics to guide and hopefully synchronize demand and supply plans. Instituting a well-run S&OP process can – and usually does – reap substantial rewards for a company, yet many businesses balk because they are hampered by a lack of understanding about how the process works.

> Showing how S&OP really has made a difference in the corporate world is what sets this book apart from those that merely describe how S&OP works, or is supposed to work.

To help fill in these gaps and give us a better grip on the subject, John Dougherty and Christopher Gray of Partners for Excellence (www.partnersforexcellence. com) have written *Sales & Operations Planning— Best Practices: Lessons Learned from Worldwide Companies*. A worthwhile addition to the literature, the book is intended to help companies benchmark and then upgrade their S&OP process. Dougherty and Gray

have drawn key lessons from a set of 13 companies that consultants have nominated as the world's best exemplars of S&OP. The book documents the methods and practices of these companies, describing in detail the ways different businesses conduct demand planning, supply planning, partnership meetings, and executive meetings. Showing how S&OP really has made a difference in the corporate world is what sets this book apart from those that merely describe how S&OP works, or is supposed to work.

The book is well organized and allows the reader to readily locate topics of interest and specific S&OP methods. Part 1, "The Companies, Sales and Operations Planning, and Results" spans five chapters and includes brief profiles of the 13 model companies, the "what and why" of S&OP, the monthly S&OP process, "hard" and "soft" benefits gained from S&OP, and lessons learned. Excerpts of these lessons are shown in Exhibit 1. For a thorough overview of S&OP, I recommend that all readers give this first section of the book a careful study.

Part 2, "Environments and Processes," examines functioning S&OP systems in various types of companies, including global supply chains, matrix

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John Mello is an Assistant Professor of Marketing at Arkansas State University and member of *Foresight*'s Editorial Board. He preceded his academic career with over 28 years in the consumer packaged goods business, including jobs in production supervision, inventory management, production planning, operations planning, materials management, and information systems implementation. John holds a PhD in Logistics from the University of Tennessee.

Exhibit 1. Lessons Learned: The ABCs of S&OP

A. People.

For communication, consensus, and teamwork to occur across all functions and levels of an organization:

1. Top management must provide leadership and support by setting high standards, providing resources, and insisting on timely completion of tasks.
2. There must be cross-functional participation and enthusiastic commitment.
3. Education must occur at all levels of the organization to ensure common understanding of objectives, principles, terminology, and required participation.

B. Accurate Information.
1. For S&OP to work, inventory, sales, forecast, production plan, and capacity data have to be made reliable.
2. Information must be presented in a focused and usable format.

C. Computer Hardware and Software.
1. Process design, not software tools, is the key to success.
2. None of the 13 best-practice companies used commercial S&OP software. Each developed their own analytical and presentation tools.

organizations, small companies, and privately held companies. Here you'll find tools for linking volume with mix of products; a discussion of the role of S&OP in lean manufacturing, total quality management, and extended supply chains; and consideration of organizational issues, financial planning, and future trends. You'll learn how to integrate S&OP with various planning tools, such as materials requirements planning, the master production schedule, and distribution requirements planning. Part 2 can be read in its entirety, or specific topics can be selected depending on need and interest.

The third section of the book presents detailed profiles of the 13 model companies, their specific approaches to S&OP, and the lessons learned at each business. A wide variety of company types, sizes, and operating characteristics are included here, and most readers ought to be able to find examples of successful S&OP practice in companies that share similarities with their own. These profiles provide an excellent means for benchmarking against other companies and offer considerable insight into different approaches to S&OP.

Of course, there are some elements of the text that could be improved. The authors credit S&OP with positive results that may also be attributable to other factors at play. Agfa Corporation, for example, experienced

significant hard benefits from S&OP, including total inventory reduction from 120 days to 40 days while continuously improving their customer service, but the authors note that "other business improvement…also played a part in achieving these benefits." I would like to have seen more specific examples of performance improvement that ties directly into S&OP, to be used as benchmarks so readers can establish reasonable expectations of what S&OP is able to deliver for their own companies. I would also have appreciated some examples of cases where things went wrong with the process, along with the early warning signs that S&OP was not working as intended or hoped.

Overall, however, readers should find this book an outstanding guide to S&OP process improvement. *Sales & Operations Planning – Best Practices* is well written, clear, and understandable. As a reference and benchmarking tool, the book delivers on its promise to provide a means to quickly identify ways in which S&OP can work in different types of companies and industries – including, very likely, your own.

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REVIEWED BY JOSEPH MC CONNELL

Coauthored by John Dougherty and Christopher Gray, two of the most accomplished educators and consultants in the S&OP field, *Sales and Operations Planning – Best Practices* (or *S&OP-BP* for short) has few equals in usefulness to practitioners of forecasting. If you want to know how to raise the forecasting function to its highest level of status and influence in an organization, while remaining confident that you are on solid ground in making your claims, this book will be your coach and friend.

The book is predominantly an empirical track record of S&OP success factors at thirteen broadly diverse companies. These are companies that have done S&OP well over many years and that have proactively navigated the ups and downs of all sorts of challenging business conditions. S&OP aligns the business with the direction demand is taking and as such elevates forecasting to a driving position as part of an integrated senior-management-owned decision process.

Because S&OP is ultimately the senior executive's handle on the business, it stands to reason that the particular audience for *S&OP-BP* is the senior executive – the general manager, president, or CEO. And while you may have read this as an assertion in other books on the subject, in *S&OP-BP* you hear it straight from the senior executives who have really lived it over the years. The book is also exhibit A for any activist in a business who sees the value of improving forecasting and S&OP but needs hard evidence to sell the project cross functionally and up the rungs of management.

During the 70s, 80s, and 90s, the focus at most companies was on supply-side improvements. Stressing productivity and efficiency was their main strategy for increasing value. That emphasis has now shifted to speeding up the rate at which companies learn and adapt in extremely competitive and international markets. This is what doing S&OP well is all about: internalized, methodical, and efficient learning and adaptation. *S&OP-BP* is the only book I know on the "before and after" of creating and following excellent S&OP, and it has come at the perfect time.

In Part I of the book, Dougherty and Gray introduce the thirteen model companies along with general S&OP concepts, process steps, benefits, and success factors. The model companies' business processes, operating environments, and industries are presented in matrix format, allowing you to immediately identify organizations with similarities to your own. As the authors cover each S&OP process step – data gathering, demand planning,

> If you want to know how to raise the forecasting function to its highest level of status and influence in an organization, while remaining confident that you are on solid ground in making your claims, this book will be your coach and friend.

Joseph McConnell is founder and CEO of McConnell Chase Software Works, which supplies software solutions in demand management and executive sales and operations planning. Joe is a frequent expert panelist at the Forecasting Summits and is a member of *Foresight*'s Practitioner Advisory Board. His colleagues have applauded his exceptional taste in Australian Shiraz.

supply planning, partnership meeting, and executive meeting – general concepts are presented, followed by notable variations in practice at the model companies.

Of particular interest is how global S&OP works in practice. The benefits section quantifies wins across a comprehensive checklist of categories: customer service, cash flow, inventory, cost reduction, capacity utilization, new-product introductions, cycle-time reductions, planning performance, data accuracy, profitability, morale, teamwork, visibility, and strategic improvement.

Part II of *S&OP-BP* covers how S&OP adapts to environments and processes. The model companies sell to a wide range of customers: mass merchandisers, retailers, distributors, wholesalers, governments, equipment manufacturers, hospitals, laboratories, companies selling consumer goods, food and beverages, and textiles. They operate as make-to-stock, make-to-order, engineer-to-order, finish-to-order, design-to-order, and with multiple order-fulfillment strategies. The authors dedicate a special section to how new-product development operates within best-practices S&OP. Full chapters are devoted to linking volume and mix, S&OP and continuous improvement through lean manufacturing and TQM/6 Sigma, S&OP and extended demand and supply chains, organizational and size issues, and S&OP and financial planning. The picture that emerges from the front lines is that

S&OP, at its best, is an organized vortex that draws in and absorbs issues, ideas, and other practices, while efficiently spinning out and ratcheting up the top issues for review and decision.

Part III of the book covers the thirteen model companies and shows how and why they're unique; topics include products and services, demand-side and supply-side practices and tools, S&OP process specifics, and hard and soft benefits.

I've listed all thirteen businesses here, in alphabetical order with revenue figures and employee count, followed by the question the authors use to introduce each:

1. **AGFA US HealthCare** / 4.2B euros / 17,000 employees: Why would a mature business with a steadily declining market demand for its base products continue employing S&OP for eleven years?

2. **Amcor Limited** / $75M (Australian) / 220 employees: Why would a small Australian site of an international packaging manufacturer need S&OP for planning products unique to each customer?

3. **Cast-Fab Technologies, Inc.** / $37M / 265 employees: Why would a small, privately held foundry and fabrication shop, producing strictly to customer order, consider their ten-year-old S&OP process key to managing their business?

4. **Coca-Cola Midi (Toulon, France)** / Revenue not given / 200 employees: They manufacture thousands of tons of products for their "captive," intracompany customers. In most cases, they are the sole supplier. So do they really need S&OP to balance demand and supply, deliver on time, and keep the inventories low?

5. **Danfoss Commercial Compressors** / 230M euros / 1,100 employees: Why is S&OP so important to a family-owned Danish company focused on global growth – one utilizing lean manufacturing, supply-chain management, and postponement (finish to order) strategy for customer order fulfillment?

6. **Eclipse, Inc.** / $90M / 500 employees: Why would

a relatively small, family-owned business, transforming itself with lean manufacturing, reengineer its ten-year-old S&OP process?

7. **Eli Lilly & Company** / $12B / 43,000 employees in 146 countries: How does a pharmaceutical company use S&OP to help launch five times as many new products as the industry average, all while adding manufacturing sites?

8. **Engineered Materials Solutions, Inc.** / $100M / 400 employees: Why would a metals processor, with a low-volume, high-mix, seasonal product line, need S&OP as well as lean manufacturing to survive a venture-capital-based leveraged buyout?

9. **Interbake Foods, LLC** / $340M / 1,700 employees: Why and how would a contract manufacturing food processor do sales and operations planning to support its highly seasonal business?

10. **Norse Dairy Systems** / $165M / 400 employees: How does S&OP operate in a company that (a) makes high-volume consumable products in a process environment, while (b) at the other end of the spectrum makes custom-designed, assembled-to-order equipment in a functional, machine-shop environment, and (c) has a direct-ship business supplied by contract manufacturers and their parent company?

11. **PYOSA S.A. (Mexico)** / $35M (U.S.) / 300 employees: How does a small, batch chemical division of a family-owned Mexican company use S&OP to manage their business?

12. **Scotts Company** / $2B / 4,000 employees: How is S&OP used in a highly seasonal company that has almost doubled its size through acquisitions and internal growth over the last fifteen years?

13. **Unicorn Medical Company (pseudonym)** / (2004) $750M / >4,000 employees: How does S&OP work in a heavily matrixed organization? Why would a company successful with lean manufacturing use S&OP?

S&OP-BP is well-organized, streamlined writing. If each of the thirteen model companies received Harvard Business School case-study treatment, the

book's length would be five times its 300+ pages. Its organization and efficiency are huge advantages for any reader, but the book is still not something to read and digest in one sitting.

Nor is it a systematic study, the kind you would expect to be heavier on data and hard analysis and lighter on anecdote; and while the book hardly lacks data – it's laden with it – the data is neither formal nor formally analyzed. The authors and contributing consultants had access to a lot more than thirteen companies; if the data were of a larger sample size and included measures of S&OP behaviors over time, the authors could have performed statistical hypothesis tests, which would have added rigor and taken the study to the next level.

Anyone in this field knows that although S&OP is no longer in its infancy, it is also far from reaching full maturity. These organizations have willingly and generously shared an enormous amount of quality information about a process they clearly see as a strategic asset. I recognize and applaud them for the significant part they have played in what John Dougherty and Christopher Gray have accomplished with *Sales and Operations Planning – Best Practices*. The authors have made a quantum contribution to S&OP literature.

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Predicting Recessions:
A Regression (Probit) Model Approach

PETER SEPHTON

PREVIEW

Forecasting recessions is fraught with difficulties: we never know if we are in recession until long after one has started. This makes it all the more important to try to predict in advance the likelihood of recession, so that businesses can plan accordingly. Peter takes us inside the economist's crystal ball, identifying key indicators of economic recession and how they can be combined into a predictive model. The model forecasts a difficult 2009.

INTRODUCTION

We economists spend much of our time biting our tongues, especially when asked about the probability of recession. There are so many factors affecting the future path of the economy that we nearly always have to condition our views by what we are assuming today, which, by the way, may be at odds with what we thought yesterday, or even an hour ago. When we hear someone pontificating over the likely state of economic affairs under this policy or that policymaker, we bristle, wishing sometimes that we had the intestinal fortitude of the weatherman.

This past year brought us new heights for oil prices, an asset-backed securities crisis and its associated contagion, a rapid rise in unemployment, and a presidential election, all of which generated renewed interest in "nowcasting" a recession – determining if and when recession began – and forecasting recessions in the future.

Because of data lags, we never know if we are in recession until long after one has started. The official

KEY POINTS

• Economic forecasters have identified many variables as potential predictors of recession. I will describe the role of five key predictors: *the interest rate spread, the credit spread, the ISM index, changes in a stock price index, and changes in the price of oil*. However, the impact of these causal factors can change from one recession to the next.

• Through a variation on a traditional regression model called a probit model, I will show how to link the probability of a recession to the behavior of these key predictors.

• As of the end of November 2008, the model suggests the United States is currently in a recession and that it will probably last into the third quarter of 2009. More rough times ahead.

recession-dating agency in the United States, the National Bureau of Economic Research, announces recession dates after looking at a wide range of economic indicators. The well-worn definition of a recession as being two successive quarterly declines in real GDP is too restrictive and incapable of capturing all of the features associated with a decline in economic activity; the NBER's approach is to look at a variety of economic indicators when dating the American business cycle (www.nber.org/cycles). While recognizing that we won't know we're in a recession until we've been in it for a while or it has passed, it is all the more important to try to predict in

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Figure 1. Interest Rate Spreads
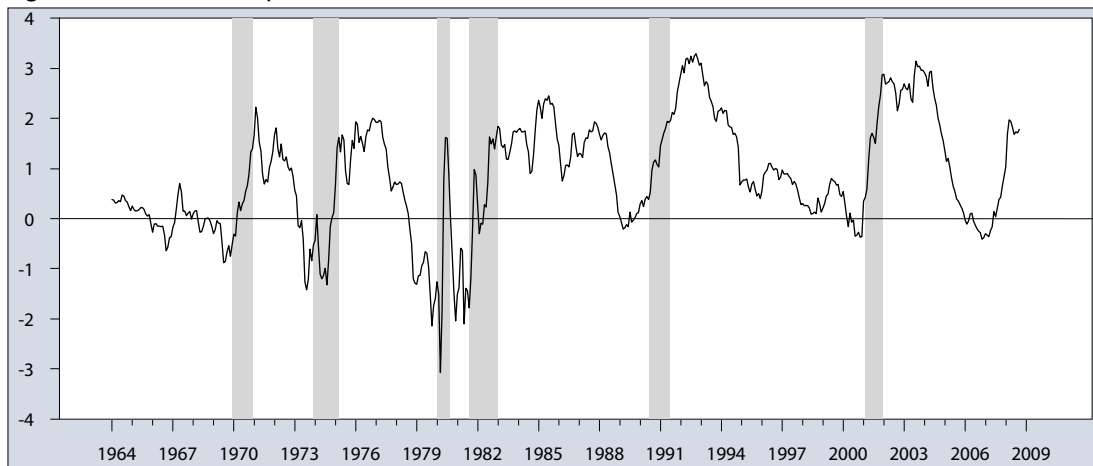
Note: The spread shown is the 10-year minus the 1-year bond rate.
Source: Series GS10-GS1 from the Federal Reserve Bank of St. Louis FRED database

advance the likelihood of recession, so that businesses can plan accordingly and policymakers can assess how best to respond should a downturn occur.

We utilize a variety of approaches to modeling recession probabilities. There is a long history of trying to construct leading indicators that signal shifts in economic activity, and in many cases these indices perform very well at capturing business-cycle turning points – periods when the economy dips into recession and then subsequently out of the trough and into recovery and expansion. Finding the "right" variables to use to construct reliable leading indicators and diffusion indicators takes judgment and experience. It's a bit like trying to follow a recipe from an old cookbook – as ingredients and the technology we use to bake the cake change, we need to adjust the mix and do some experimenting to get it "just right." Creating leading indicators is a somewhat similar process, although usually not as tasty.

More generally, when economists try to forecast the likelihood of recession, we use a wide range of techniques and methods. Some involve computationally intensive algorithms linking various economic indicators, while others rely on measurements of anxiety in markets, Delphi groups, surveys, and even flipping coins and tarot cards. My purpose in this article is to use a traditional regression model to see if we can link

the probability of a recession to information we think might play a predictive role. I'm not suggesting this is the best approach to use – it's just one of the available methods in the economist's toolbox – so let's see how well this approach does at forecasting recession.

RECESSION PREDICTORS

The official dates of the last few recessions in the United States are illustrated by the shaded regions in Figure 1:

December 1969 to November 1970
November 1973 to March 1975
January 1980 to July 1980
July 1981 to November 1982
July 1990 to March 1991
March 2001 to November 2001

Interest Rate Spread: Many econometric modelers have found that the interest rate spread – the difference between a long-term interest rate and a short-term rate – does a good job at predicting recession. Normally, long-term rates are higher than short-term rates. But when the interest rate spread turns negative, it is usually a sign that recession is expected soon.

The explanation for the effect of the interest rate spread usually relies on the idea that policy interest rates, which are at the short end of the maturity spectrum, fall when central bankers want to stimulate the

Figure 2. Interest Rate Spreads
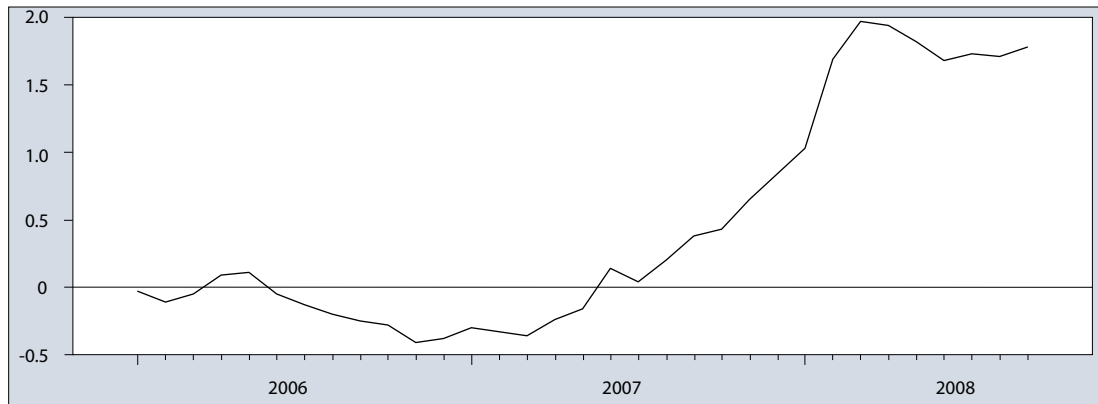
economy. If the market expects short-term rates to fall, interest rate arbitrage between short-term and long-term instruments will drive the long-term interest rate below the current short-term rate, leading to a negative spread. And when would the market expect policy interest rates to fall? When it senses that the central bank sees excessive slack in the economy, hence an impending economic downturn or recession. Figure 1 shows that the spread has become negative before each of the last six recessions.

Figure 2 shows that the spread became negative in 2006 and 2007. Market commentary at the time indicated a recession was on its way, but that recession never materialized – until perhaps now. This suggests that a negative spread might not *always* foretell a recession, but if it walks like a duck and it quacks like a duck ... it's probably a duck.

Other variables that are considered to have predictive power include:

• **The credit spread**: the difference between returns on low-grade and high-grade securities. A higher credit spread may reflect increasing concerns over future economic activity.

• **The ISM (Institute for Supply Management) production index** (formerly known as the Purchasing Managers' Index). An index value below 50 signals an expected contraction in production.

• **Changes in the inflation-adjusted value of stock prices**. Lower real-stock valuations can portend distress in markets.

• **The effective federal funds rate**, which measures the stance of monetary policy. Lowering of rates indicates an effort by the Fed to stimulate the economy.

• **Price of oil**. Given its recent behavior, one might consider that changes in the price of oil may also provide insight into the likelihood of recession, so it too will be considered as a potential predictor of the probability of recession.

All these data are freely available for download from the St. Louis Federal Reserve Bank's FRED database (http://research.stlouisfed.org/fred2) and the Institute for Supply Management's website (www.ism.ws/ISMReport). The series identifiers in FRED include FEDFUNDS, (GS10-GS1), (BAA-AAA), OILPRICE, SP500 and PCEPI, and the ISM index (PMI).

In Figure 3, it is clear that these potential recession predictors are correlated with past U.S. recessions. Real stock prices appear to fall just before a recession, and the effective federal funds rate seems to decline before each recession, perhaps capturing the anticipatory policy response. The ISM index starts falling long before the recession begins and appears to rise above 50% shortly after the recession is over. Oil prices, though, seem to have a varying pattern before and

after recessions. In the 1970s and in the early 1990s, prices rose before and during the recession. In the early 1980s and the recession of 2001, oil prices rose before the recession; then, once the economy slipped into decline, oil prices fell.

THE PROBLEM OF
SHIFTING CAUSAL FACTORS

The question of the "right" combinations of variables to provide an effective recession forecasting model has puzzled economists for years. One problem is that different causal factors appear to have been at play from one recession to the next. In the early 1970s, widespread drought caused significant shocks to world food output while economies were stressed by oil price spikes and stagflation. The recession of the early 1990s was primarily the result of restrictive monetary policies aimed at restraining inflation, while that of 2001 was generally thought to be the result of aftereffects from the tech meltdown as well as a reduction in U.S. net exports (Walsh [1993], Kliesen [2003]).

So how do economists decide which variables to include in their forecasting models? As with most questions in economics, the answer is, "It depends." Are we trying to build a model that will forecast the 2001 recession (and the post-recession expansion)? If so, it makes sense to fit the relationships from the mid-1980s until 2000 and then ask how well the model forecast into 2001 and 2002, the period after onset of recession but before recovery began. If we're trying to build a model to forecast whether there will be recession in 2009, then using data from the mid-1980s through 2008 makes sense. One important caveat is that there's no reason to assume the structure of economic relationships remains fixed over time, so the variables giving the best model on data until mid-2008 might be much different from those giving the best model to use to explain the 2001 recession.

Another wrinkle in the modeling process is that economic data are frequently revised. That's one reason why economists put financial variables such as interest rates and asset prices into their recession forecasting models, because these variables are rarely revised. As an example, consider the preliminary estimates of real GDP growth released by the Bureau of Economic Analysis for the second quarter of 2008. The initial estimate of 3.3 percent was revised down to 2.8 percent in late September 2008 as more data became available. While only half of one percent, media reports immediately cited the increased risk of

Figure 3. Predictive Variables
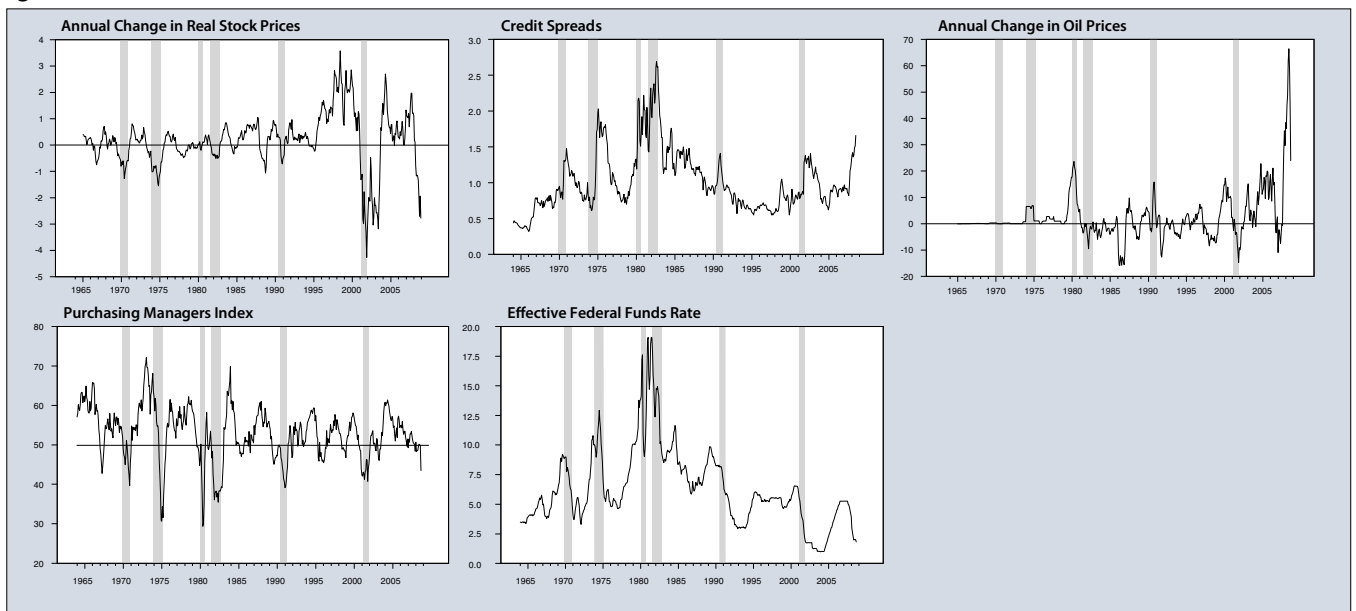
recession (Englund & MacDonald, 2008). Financial data are not usually subject to these data revisions, and to the extent that markets are efficient, asset prices and returns data should reflect all available information.

Because these key variables frequently change, it is necessary that we economists test our forecasting models to see if they are structurally stable – that is, are the effects of the causal variables consistent over time? For the most part, simple forecasting models are not structurally stable, so that models that do well today will not do well tomorrow. The economist then must continually update the models as new data come in.

A PROBIT MODEL

Probit models are a common approach to predicting recession. A probit model allows us to determine the probability of an event (recession) that either will or won't occur. Statisticians call such an event a "dichotomous dependent variable" and use the values "one" or "zero" to indicate whether we are or are not in recession. Equation (1) is an illustrative probit model for predicting the probability of recession:

In equation (1) below, the left-hand term is the probability of recession twelve months from now, while the right-hand terms are the causal factors.

ISpread denotes the interest rate spread between one-year and ten-year constant maturity government bonds at time t.

CSpread denotes the spread between Moody's long-term (30-year) Baa and Aaa seasoned corporate bond yields at time t.

Oil denotes the year-over-year change in West Texas Intermediate Crude oil at time t.

RSP500 denotes the year-over-year change in the S&P500 index, deflated by the price of consumer expenditures, at time t.

FF_t denotes the effective federal funds rate at time t.

ISM_t denotes the ISM index (as previously noted, formerly the Purchasing Managers' Index) at time t.

The probit model assumes the errors in the equation follow the standard normal distribution, your typical statistical assumption.

Using monthly data spanning from January 1986 until September 2008, the probit model appears to capture the probability of recession fairly well on a historical basis. The estimated model is equation (2), below.

Each coefficient is statistically, significantly different from zero, at or about the ten percent level of significance.

For any time period, once values are entered for the six explanatory variables, the equation yields a probability of recession. For example, plugging in the values for June 2007 data on the right-hand side of the equation leads to a predicted probability of recession in June 2008 of nearly 29%. In Figure 4, we plot the probabilities over the 1986-2008 period. Notice the horizontal line drawn at 0.5. Values above this line indicate that the model is saying that recession has more than a 50-50 chance of occurring.

Figure 4 indicates that the recession-probability estimates from this model captured the recession in the early 1990s quite well. It also predicted the 2001 recession with a bit of a lag, since the actual start

Equation 1:
$$\Pr(Recession_{t+12}) = \Phi\{\alpha_1 + \alpha_2\, ISpread_t + \alpha_3\, CSpread_t + \alpha_4 Oil_t + \alpha_5 RSP500_t + \alpha_6 FF_t + \alpha_7 ISM_t\} \quad (1)$$

Equation 2:
$$\Pr(Recession_{t+12}) = \Phi\{6.03 - 2.22\, ISpread_t - 2.04\, CSpread_t + 0.16 Oil_t + 0.63 RSP500_t + 0.54 FF_t - 0.20 ISM_t\} \quad (2)$$

Figure 4. Recession Probabilities

might come from a model that continually updates the probability of recession based on both new data and new estimates of the parameters in the probit model. In this way, we explicitly account for structural change in our equation, and we allow the most recent data to color our views of the probability of recession.
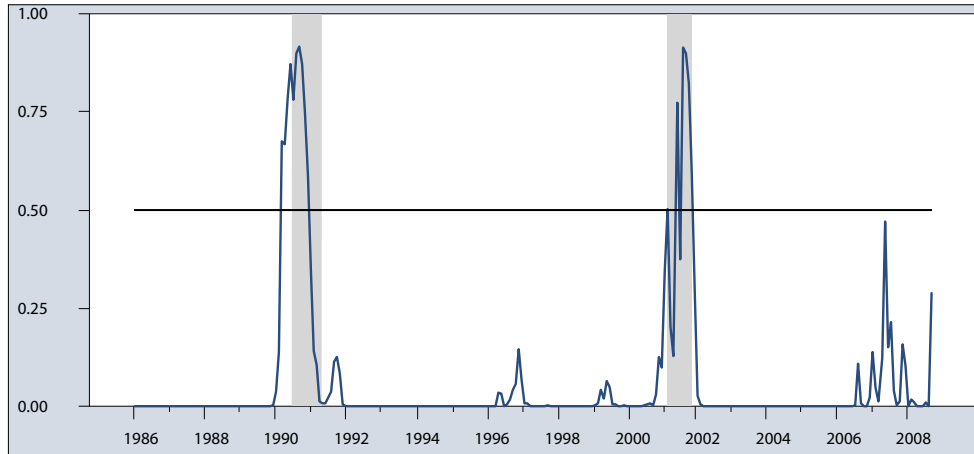
date of the recession appears to predate the time at which the recession-probability forecast passes the 50% threshold. At that time, using the available data, some forecasters were able to predict the recession with greater precision. For example, in September 2000 the Economic Cycle Research Institute (www. businesscycle.com) reported that the U.S. Leading Diffusion Index was falling and most likely signalling that a recession would soon follow.

THE CURRENT RECESSION

The probit model's signal of recession for 2008 using data up to September 2007 did not reach 50% (the horizontal line). Remember, we are predicting the probability of recession in the next twelve months, so the predicted recession probability for September 2008 uses data up to September 2007. Recession probabilities peaked in May 2007 at 47%, with any confidence interval around that point prediction including values above 50%, so one might conclude the model is allowing for the possibility of recession. As of November 2008, the NBER had not yet dated additional business-cycle turning points, so we will have to wait and see.

As I have noted, the causal factors underlying recessions have most certainly changed over time. A more realistic probability forecast

Toward this end, I estimated the probit model from January 1986 until January 1998, constructed the probability of recession estimate for January 1999, then updated the dataset to February 1998 and reestimated the model to calculate the probability of recession in February 1999, and so on, up to the most recent data of September 2008. This approach predicts the probability of recession through September 2009. Figure 5 presents these estimated "rolling" recession probabilities. The model appears to have captured the 2001 recession with a bit of a lag and predicted recession in 2007 – a result which the NBER could still confirm after having analyzed the historical record. There appear to be two "false signals" in the late 1990s, although these may be related to the volatility we saw in markets during the run up to, and eventual bursting of, the tech bubble.

Figure 5. Updated Recession Probabilities
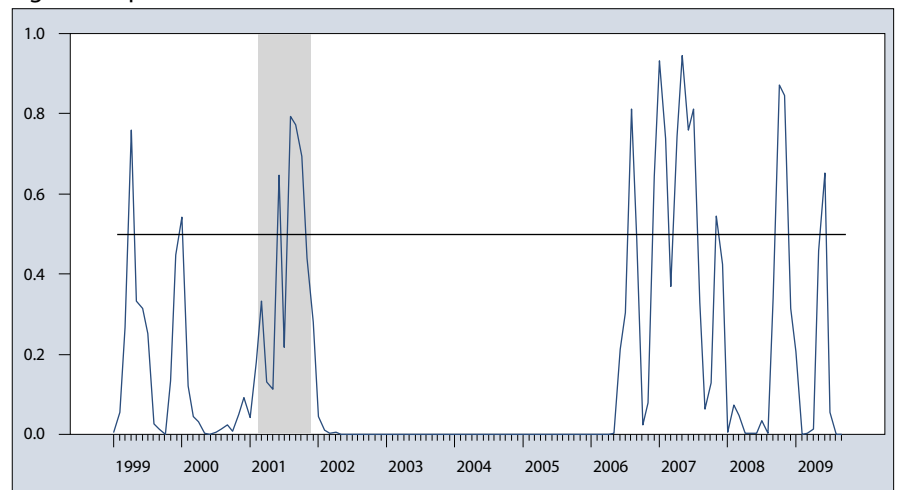
Figure 6. Updated Recession Probabilities 2008-2009
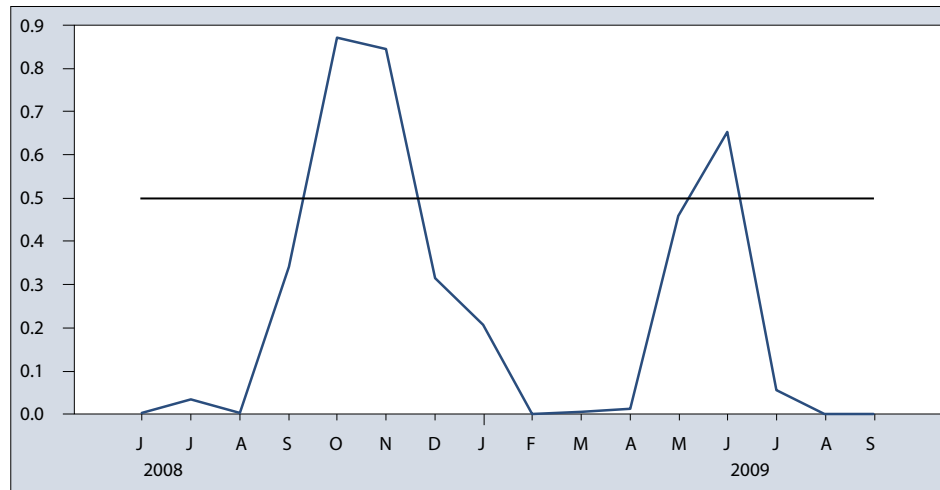
Figure 6 highlights the probability forecasts for 2008-2009. The estimates suggest the United States is currently in a recession and that it will probably last into the third quarter of 2009. (Ed. Note: In early December 2008, the NBER declared that the U.S. economy has been in recession since December 2007.)

A similar prediction comes from Nyberg (2008). Using somewhat more sophisticated versions of the simple probit model examined here, Nyberg predicted a high likelihood of recession in the United States in early 2008. On the other hand, similar models applied by Muhl (2008) predicted (as of February 2008) a very low likelihood of recession in Switzerland into 2008. Unfortunately, as we all know too well, global economic conditions can quickly change with little warning.

These findings suggest that the search for reliable predictors of recession should be viewed as a never-ending story and that economists should mete out our forecasts with humility.

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New Evidence on the Value of Combining Forecasts

PAUL GOODWIN

One of the major findings of forecasting research over the last quarter century has been that greater predictive accuracy can often be achieved by combining forecasts from different methods or sources. Combination can be a process as straightforward as taking a simple average of the different forecasts, in which case the constituent forecasts are all weighted equally. Other, more sophisticated techniques are available too, such as trying to estimate the optimal weights that should be attached to the individual forecasts, so that those that are likely to be the most accurate receive a greater weight in the averaging process. Researchers continue to investigate circumstances where combining may well be useful to forecasters and to compare the accuracy of different approaches to combining forecasts.

FORECAST COMBINATION AND THE BANK OF ENGLAND'S SUITE OF STATISTICAL FORECASTING MODELS

George Kapetanios and his colleagues (Kapetanios et al., 2008) have recently evaluated the potential advantages of combining forecasting data at the Bank of England, where quarterly forecasts of inflation and GDP growth are made. The bank has a suite of different statistical forecasting methods available. They include extremely simple approaches, such as the naïve (or random walk) method where the forecasts are equal to the most recent observation. More sophisticated and complex methods in the suite include autoregression, vector-autoregressions (VARs), Markov switching models, factor models, and time-varying coefficient models.

The researchers assessed the value of combining forecasts from the methods available using two different approaches. The first involved taking a simple mean of the forecasts generated by the methods in the suite. The second involved weighting the individual forecasts based upon the Akaike information criterion (AIC). Many commercial forecasting packages report the AIC, which is a measure that takes into account how well a model fits past data but also penalizes the model for complexity, based on the number of parameters it contains. Thus forecasts from relatively simple models that provided a good fit to past observations received a greater weight in the averaging process than more complex or poorer fitting models.

The accuracy of the two types of combined forecasts was assessed over a range of forecast horizons using the relative root mean squared error (RRMSE) statistic. This compares the square root of the sum of squared forecast errors to those of a benchmark forecasting method (in this case, the benchmark was the autoregressive forecast). The researchers reported that "it is striking that forecast performance…is improved when forecasts are combined and the best forecast combinations for both growth and inflation are those based on the [Akaike] information criterion." The Kapetanios group concluded that "combinations of statistical forecasts generate good forecasts of the key macroeconomic variables we are interested in."

Similar benefits of combining have also recently been reported in studies by David Rapach and Jack Strauss (Rapach & Strauss, 2008), who forecast U.S. employment growth, and Jeong-Ryeol Kurz-Kim (Kurz-Kim, 2008), who forecasts U.S. GDP growth. The latter study combined forecasts from the same method (autoregression) that was implemented in different ways.

WHY DID COMBINING WORK?

The researchers suggest a number of reasons. Different models use different sets of information, and each model is likely to represent an incomplete view of the process that is driving the variable of interest. Combined forecasts are therefore able to draw on a wider set of information. In addition, some of the constituent forecasting methods may be biased, in that they consistently forecast too high or too low. When several methods are combined, there is a likelihood that biases in different directions will counteract each other, thereby improving accuracy.

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TRIMMED MEANS

While the more sophisticated AIC-based weights performed best in the Kapetanios et al. study, the simple mean also did well in both this and the Rapach and Strauss study. The simple mean does have advantages. For one thing, it is easy to implement and explain. It also avoids the need to estimate the optimum set of weights to attach to the forecasts – in many practical circumstances, there may be insufficient data to reliably make these estimates.

However, the simple mean also has the disadvantage of being sensitive to extreme forecasts: if there is an outlying forecast in the set that is being averaged, it will have undue influence on the combined forecast. This has led some researchers (e.g., Armstrong, 2001) to argue that the highest and lowest forecasts should be removed from the set before the mean is calculated. The resulting average is called a *trimmed mean*.

Victor Jose and Robert Winkler (Jose & Winkler, 2008) recently investigated whether trimmed means lead to more accurate combined forecasts. They explored the effects of applying different degrees of trimming (e.g., removing the two highest and two lowest forecasts from the set before averaging, or the three highest and three lowest, and so on). In addition, they evaluated whether an alternative form of averaging, the *Winsorized mean*, was more effective. Rather than removing the highest and lowest forecasts, the Winsorized mean alters their values, making them equal to the highest and lowest forecast values that remain. For example, consider these sales forecasts from five different methods:

> When you have access to forecasts from **different** sources or methods (e.g., different statistical methods or judgmental forecasts from different experts), **combining** these forecasts is likely to be an effective way of improving accuracy.

23, 34, 47, 53, 86. If we decide to leave off the two "outside" forecasts, our trimmed mean will be the mean of 34, 47, and 53 (i.e., 44.7). In contrast, the Winsorized mean will be the mean of 34, 34, 47, 53, and 53 (i.e., 44.2). It is quickly apparent that these two types of modification only make sense when you have at least three forecasts to work with. Also, the two methods yield differing results only when there are a minimum of five forecasts to combine.

The researchers tested these approaches by combining the forecasts of 22 methods for the 3003 time series from the M3 competition (Makridakis & Hibon, 2000). Additionally, they carried out similar tests on the quarterly nominal GDP forecasts from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. They found that both trimming and Winsorization yielded slightly more accurate forecasts than the simple mean; they also outperformed all of the individual forecasting methods. There was, however, little to choose between trimming and Winsorization. Moderate degrees of trimming, removing 10 to 30% of the forecasts, seemed to work best. For Winsorization, replacing 15 to 45% of the values appeared to be most effective. I would point out that greater amounts of trimming or replacement yielded greater accuracy when there was more variation in the individual forecasts. This is probably because highly variable sets of forecasts contained extreme values.

CONCLUSIONS

All of this suggests that when you have access to forecasts from different sources or methods (e.g., different statistical methods or judgmental forecasts from different experts), combining these forecasts is likely to be an effective way of improving accuracy. Even using relatively simple combination methods will be enough to yield improvements in many cases. Whatever your area of forecasting, combining forecasts is certainly worth a long, close look.

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Percentage Error: What Denominator?

FINDINGS OF A SURVEY CONDUCTED BY KESTEN GREEN AND LEN TASHMAN

THE ISSUE

This is our second survey on the measurement of forecast error. We reported the results of our first survey in the Summer 2008 issue of *Foresight* (Green & Tashman, 2008). The question we asked in that survey was whether to define forecast error as Actual minus Forecast (A-F) or Forecast minus Actual (F-A). Respondents made good arguments for both of the alternatives.

In the current survey, we asked how *percentage forecast error* should be measured. In particular: What should the denominator be when calculating percentage error?

We posed the question to the International Institute of Forecasters discussion list as well as to *Foresight* subscribers, in the following way:

> To calculate a percentage error, it is better to use…
>
> (*Check or write in*)
>
> 1. The actual value (A) as the denominator   [   ]
> 2. The forecast (F) as the denominator   [   ]
> 3. Neither (A) nor (F) but some other value   [   ]
>
> I recommend my choice of denominator, because:
> _____

The first two options in the questionnaire have each been used when calculating the mean absolute percentage error (MAPE) for multiple forecast periods. The first option is the more traditional form.

One popular alternative to using either A or F as the denominator is to take an average of the two: (A+F)/2. Calculated over multiple forecast periods, this measure is most commonly called the symmetric MAPE (sMAPE) and has been used in recent forecasting competitions to compare the accuracy of forecasts from different methods. See, for example, www.neural-forecasting-competition.com/index.htm.

SURVEY RESULTS

We received 61 usable responses. 34 of these (a majority of 56%) preferred option 1: using the **Actual** as the denominator for the percentage error. 15% preferred option 2, using the **Forecast** as the denominator, while 29% chose option 3, something other than the actual or the forecast.

One respondent wrote: "*For our company, this issue led to a very heated debate with many strong points of view. I would imagine that many other organizations will go through the same experience.*"

Option 1
Percentage Error = Error / Actual * 100

Of the 34 proponents of using the Actual value for the denominator, 31 gave us their reasons. We have organized their responses by theme.

A. The Actual is the forecaster's target.
Actual value is the forecast target and therefore should represent the baseline for measurement.

The measure of our success must be how close we came to "the truth."

Actual is the "stake in the ground" against which we should measure variance.

Since forecasting what actually happened is always our goal, we should be comparing how well we did to the actual value.

We should measure performance against reality.

B. The Actual is the only consistent basis for comparing forecast accuracy against a benchmark or for judging improvement over time.

Actual is the only acceptable denominator because

it represents the only objective benchmark for comparison.

Without a fixed point of reference quantity in the denominator, you will have trouble comparing the errors of one forecast to another.

You want to compare the forecast to actuals and not the other way around. The actuals are the most important factor. It drives safety stock calculations that are based on standard deviation of forecast error calculations that use actuals as the denominator.

Forecast error is measured here as (actual-forecast)/ actual, for comparability to other studies.

C. The Actuals serve as the weights for a weighted MAPE.

Using the Actuals is more consistent for calculating a weighted average percentage error (WAPE) for a group of SKUs or even for the full product portfolio. Using actual value as denominator is providing the weight for the different SKUs, which is more understandable – one is weighting different SKUs based on their actual contribution. If we use F (forecast), this means we will weigh them based on the forecast – but this can be challenged as subjective. Someone may calculate the single SKU accuracy based on F as denominator, and then weigh according to Actual sales of each SKU, but this unnecessarily complicates the formula.

D. The Actual is the customary and expected denominator of the MAPE.

I would argue that the standard definition of "percent error" uses the Actual. The Actual is used without any discussion of alternatives in the first three textbooks I opened, it is used in most forecasting software, and it is used on Wikipedia (at least until someone changes it).

If you are creating a display that reads "percent error" or "MAPE" for others to read without further explanation, you should use Actual – this is what is expected.

Actual is the generally used and accepted formula; if you use an alternative, such as the Forecast, you might need to give it a new name in order to avoid confusion.

E. Use of the Actual gives a more intuitive interpretation.

If the forecast value is > the actual value, then the percentage error with the forecast in the denominator cannot exceed 100%, which is misleading. For example, if the Actual is 100 and the Forecast is 1,000, the average percentage error with Actual is 900% but with Forecast is only 90%. (Ed. note: See Table 1a for an illustrative calculation.)

The reason is pragmatic. If Actual is, say, 10 and Forecast is 20, most people would say the percentage error is 100%, not 50%. Or they would say forecast is twice what it should have been, not that the actual is half the forecast.

By relating the magnitude of the forecast error to an Actual figure, the result can be easily communicated to non specialists.

From a retail perspective, explaining "over-forecasting" when Forecast is the denominator seems illogical to business audiences.

F. Using the Forecast in the denominator allows for manipulation of the forecast result.

Utilizing the Forecast as the benchmark is subjective and creates the opportunity for the forecaster to manipulate results.

Use of the Actual eliminates "denominator management."

Using Forecast encourages high forecasting.

G. Caveats: There are occasions when the Actual can't be used.

Use of Actual only works for non-0 values of the Actual.

Table 1. Illustrative Calculations

A	F	Absolute Error	% Error with A	% Error with F	Avg A+F	% Error with Avg of A&F
1a. If the Forecast exceeds the Actual, the % error cannot exceed 100%.						
100	200	100	100%	50%	150	0.667
100	1000	900	900%	90%	550	164%
100	10000	9900	9900%	99%	5050	196%
1b. Illustration of the Symmetry of the sMAPE.						
100	50	50	50%	100%	75	67%
50	100	50	100%	50%	75	67%
1c. When the Actual equals zero, use of sMAPE always yields 200%.						
0	50	50	#DIV/0!	100%	25	200%
0	100	100	#DIV/0!	100%	50	200%

If you are trying to overcome difficulties related to specific data sets (e.g., low volume, zeroes, etc.) or biases associated with using a percentage error, then you may want to create a statistic that uses a different denominator than the Actual. However, once you do so, you need to document your nonstandard definition of "percentage error" to anyone who will be using it.

For me, the Actual is the reference value. But in my job I deal with long-term (5-10 years+) forecasts, and the Actual is seldom "actually" seen. And since you're asking this question, my suspicion tells me the issue is more complicated than this.

Option 2
Percentage Error = Error / Forecast * 100

Eight of the 9 respondents who preferred to use the Forecast value for the denominator provided their reasons for doing so. Their responses fell into two groups.

A. Using Forecast in the denominator enables you to measure performance against forecast or plan.

For business assessment of forecast performance, the relevant benchmark is the plan – a forecast, whatever the business term. The relevant error is percent variation from plan, not from actual (nor from an average of the two).

For revenue forecasting, using the Forecast as the denominator is considered to be more appropriate since the forecast is the revenue estimate determining and constraining the state budget. Any future budget adjustments by the governor and legislature due to changing economic conditions are equal to the percentage deviations from the forecasted amounts initially used in the budget. Therefore, the error as a percent of the forecasted level is the true measure of the necessary adjustment, instead of the more commonly used ratio of (actual-forecast)/actual.

It has always made more sense to me that the forecasted value be used as the denominator, since it is the forecasted value on which you are basing your decisions.

The forecast is what drives manufacturing and is what is communicated to shareholders.

You are measuring the accuracy of a forecast, so you divide by the forecast. I thought this was a standard approach in science and statistics.

If we were to measure a purely statistical forecast (no qualitative adjustments), we would use Actual value (A) as the denominator because statistically this should be the most consistent number. However, once qualitative input (human judgment) from sales is included, there is an element that is not purely statistical in nature.

For this reason, we have chosen to rather divide by forecast value (F) such that we measure performance to our forecast.

B. The argument that the use of Forecast in the denominator opens the opportunity for manipulation is weak.

The politicizing argument is very weak, since the forecast is in the numerator in any case. It also implies being able to tamper with the forecast after the fact, and that an unbiased forecast is not a goal of the forecasting process.

Option 1 or 2
Percentage Error = Error / [Actual or Forecast: It Depends] * 100

Several respondents indicated that they would choose A or F, depending on the purpose of the forecast.

Actual, if measuring deviation of forecast from actual values. Forecast, if measuring actual events deviated from the forecast.

If the data are <u>always</u> positive and if the zero is meaningful, then use Actual. This gives the MAPE and is easy to understand and explain. Otherwise we need an alternative to Actual in the denominator.

The actual value must be used as a denominator whenever comparing forecast performance over time and/or between groups. Evaluating performance is an assessment of how close the forecasters come to the actual or "true" value. If forecast is used in the denominator, then performance assessment is sullied by the magnitude of the forecasted quantity.

If Sales and Marketing are being measured and provided incentives based on how well they forecast, then we measure the variance of the forecast of each from the actual value. If Sales forecast 150 and Marketing forecast 60 and actual is 100, then Sales forecast error is (150-100)/150=33% while Marketing forecast error is (70-100)/70=43%. When Forecast is

the denominator, then Sales appears to be the better forecaster – even though their forecast had a greater difference to actual.

When assessing the impact of forecast error on deployment and/or production, then forecast error should be calculated with Forecast in the denominator because inventory planning has been done assuming the forecast is the true value.

Option 3
Percentage Error = Error / [Something Other Than Actual or Forecast] * 100

One respondent indicated use of Actual or Forecast, whichever had the higher value. No explanation was given.

Three respondents use the average of the Actual and the Forecast.

Averaging actual and forecast to get the denominator results in a symmetrical percent-error measure. (Ed. note: See Table 1b for an illustration, and the article by Goodwin and Lawton (1999) for a deeper analysis of the symmetry of the sMAPE.)

There likely is no "silver bullet" here, but it might be worthwhile to throw into the mix using the average of F and A – this helps solve the division-by-zero issues and helps take out the bias. Using F alone encourages high forecasting; using A alone does not deal with zero actuals. (Ed. note: Unfortunately, the averaging of A and F does not deal with the zero problem. When A is zero, the division of the forecast error by the average of A and F always results in a percentage error equal to 200%, as shown in Table 1c below and discussed by Boylan and Syntetos [2006].)

I find the corrected sMAPE adequate for most empirical applications without implying any cost structure, although it is slightly downward biased. In company scenarios, I have switched to suggesting a weighted MAPE (by turnover, etc.) if it is used for decision making and tracking.

Four respondents suggest use of some "average of Actual values" in the denominator.

Use the mean of the series. Handles the case of intermittent data, is symmetrical, and works for cross section. (Ed. note: This recommendation leads to use of the MAD/Mean, as recommended by Kolassa and Schutz [2007].)

My personal favorite is MAD/Mean. It is stable, even for slow-moving items, it can be easily explained, and it has a straightforward percentage interpretation.

A median baseline, or trimmed average, using recent periods, provides a stable and meaningful denominator.

I prefer a "local level" as the denominator in all the error % calculations. (Ed. note: The local level can be thought of as a weighted average of the historical data.) *When using Holt-Winters, I use the level directly, as it is a highly reliable indication of the current trading level of the time series. In addition, it isn't affected by outliers and seasonality. The latter factors may skew readings (hence interpretations) dramatically and lead to incorrect decisions.*

With other types of forecasting – such as multivariate – there's always some "local constant" that can be used. Even a median of the last 6 months would do. The main problem that arises here is what to do when this level approaches zero. This – hopefully – does not happen often in any set of data to be measured. It would rather point, as a diagnostic, to issues other than forecasting that need dire attention.

Two respondents recommend that the denominator be the absolute average of the period-over-period differences in the data, yielding a MASE (Mean Absolute Scaled Error).

The denominator should be equal to the mean of the absolute differences in the historical data. This is better, for example, than the mean of the historical data, because that mean could be close to zero. And, if the data are nonstationary (e.g., trended), then the mean of the historical data will change systematically as more data are collected. However, the mean of the absolute differences will be well behaved, even if the data are nonstationary, and it will always be positive. It has the added advantage of providing a neat, interpretable statistic: the MASE. Values less than 1 mean that the forecasts are more accurate than the in-sample, naïve, one-step forecasts.* (See Hyndman, 2006.)

Mean absolute scaled error, which uses the average absolute error for the random walk forecast (i.e., the absolute differences in the data).

FOLLOW-UP

We welcome your reactions to these results. Have they clarified the issue? Have they provided new food for thought? Have they changed your mind? See our contact information at bottom.

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Combined Forecasts of the 2008 Election: The Pollyvote

ANDREAS GRAEFE, J. SCOTT ARMSTRONG, ALFRED G. CUZÁN, AND RANDALL J. JONES, JR.

PREVIEW

At **PoliticalForecasting.com,** **better known as the Pollyvote, the authors combine forecasts from four sources:** **election polls,** **a** **panel of American political experts,** **the** **Iowa Electronic Market,** **and** **quantitative models.** **The day before the election, Polly predicted that the Republican ticket's share of the two-party vote would be 47.0%. The outcome was close at 46.6% (as of the end of November). In his Hot New Research column in this issue, Paul Goodwin discusses the benefits of combining forecasts. The success of the Pollyvote should further enhance interest is this approach to forecasting.**

INTRODUCTION

In this year's presidential election, as in 2004, the Pollyvote applied the evidence-based principle of combining all credible forecasts (Armstrong, 2001) to predict the election outcome. Pollyvote is calculated by averaging within and across four components, all weighted equally, to forecast the incumbent party's share of the two-party vote. The components were updated on a daily basis, or whenever new data became available, and included:

- Combined trial-heat polls (using the RCP poll average from realclearpolitics.com)
- A seven-day rolling average of the vote-share contract prices on the Iowa Electronic Market (IEM)
- 16 quantitative models
- A survey of experts on American politics

PERFORMANCE OF THE POLLYVOTE

Polly's performance was impressive. From August 2007 through the eve of the election, the Pollyvote

THE POLLYVOTE TEAM

Andreas Graefe   J. Scott Armstrong   Alfred G. Cuzán   Randall J. Jones, Jr.

consistently predicted that Barack Obama would win the White House – even just following the conventions when combined polls, poll projections (such as fivethirtyeight.com), and prediction markets indicated at times that John McCain was ahead.

The same was true in 2004, when Polly consistently predicted George Bush as the winner, despite John Kerry's short-term lead in polls and markets. This year's final Polly forecast, issued on the day before the election, missed the actual outcome by 0.4 percentage points. Across the entire forecast horizon, the mean absolute error (MAE) was 1.6 percentage points. By comparison, the corresponding percentage point errors in 2004 were 0.3 and 0.5, respectively.

Comparing the Pollyvote with two other closely followed indicators, Real Clear Politics' average on election eve was off by 0.5 percentage points, and by 1.8 percentage points across the entire forecast horizon. The 'original' IEM (without calculating 7-day rolling averages), was off by 0.2 and 1.7, respectively. The RCP wrongly predicted John McCain as the winner on 41 days, and the IEM did so on 10 days.

Interestingly, the performance of the Pollyvote components was different in 2008, compared with 2004. Ranked in terms of most-to-least-accurate across the entire forecast horizon, the 2004 ranking was the IEM's most accurate, followed by the polls, the experts, and the quantitative models. This year, again over the entire forecasting horizon, the models led in accuracy, followed by the experts, the IEM and the polls. The finding that the combined Pollyvote forecasts for the two elections were almost equally accurate supports the decision to weight the components equally, rather than differentially.

In a change from the previous presidential election, this year the Pollyvote incorporated *damping* to reduce measurement error in polls. This technique makes forecasts more conservative in situations involving high uncertainty. Applying it in 2008 seemed appropriate, because polls have been found to overestimate support for the front-runner, especially early in the campaign (Campbell, 1996). Campbell provides a damping formula, which we used to discount the polls' spread between the candidates, proportionate to the time remaining until election day. The longer the time until the election, the larger the discount applied to the front-runner's margin.

> The Pollyvote was designed to demonstrate the power of combining forecasts. Many forecasters overlook the combining principle, even though more than thirty studies have shown that it greatly improves forecast accuracy.

Measured over the entire forecast horizon, the MAE for the damped polls was 2.7 percentage points vs. 1.8 for the original RCP average. The overall Pollyvote MAE increased from 1.3 to 1.6. From this result, which ran contrary to expectations, we conclude that further analysis is necessary to more effectively apply damping in election forecasting.

THE POWER OF COMBINING

The number of quantitative models utilized in the Pollyvote increased in 2008 to 16 from the 10 used in 2004. Some of the new models brought new methods and data into the mix. For example, Polly added three models that use a segmentation approach by aggregating state-level polls, and two others that employ an index method. One of the latter, the PollyIssues model, represents an innovation: it assumes that voters choose the candidate they believe will better handle the country's problems (Graefe & Armstrong, 2008).

Adding additional models constructed by different methods may have been responsible for the superior performance of the quantitative model component this year. As has been shown by Armstrong (2001), combining forecasts is particularly valuable if you use methods that differ substantially and draw from different sources of information.

The Pollyvote was designed to demonstrate the power of combining forecasts. Combining yields a forecast error which is never larger, and normally is substantially smaller, than the error of the typical forecasts of the components. Still, many forecasters overlook the combining principle, even though more than thirty studies have shown that it greatly improves forecast accuracy. A large part of the problem could be that combining defies intuition. As demonstrated by Larrick and Soll (2006) in a clever series of experiments, a majority of highly intelligent people did not understand the value of combining. As a result, combining is not used nearly as much as it should be in forecasting. People simply think that they can forecast better on their own.

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Forecasting Performance of Regression Models in the 2008 Presidential Election

RANDALL J. JONES, JR. AND ALFRED G. CUZÁN

Table 1.

Regression Forecasts of the Democratic Party Share of the Two-Party Vote in the 2008 Presidential Election. Actual outcome was 53.4%.*			
Forecaster	**Date of original forecast**	**Forecast**	**Error (- is underforecast)****
Ray Fair***	July 31 (Oct 31)	51.5 (51.9)	-1.9 (-1.5)
Alan Abramowitz	August 28	54.3	0.9
Christopher Wlezien & Robert Erikson	August 28	52.2	-1.2
James Campbell	Sept 8 (Oct 15)	47.3 (51.1)	-6.1 (-2.3)
Allan Lichtman	August 7, 2007	54.0	0.6
Helmut Norpoth	January 15	50.1	-3.3
Douglas Hibbs	June 7 (Oct 31)	51.8 (53.7)	-1.6 (0.3)
Carl Klarner	July 28	53.0	-0.4
Alfred G. Cuzán & Charles M. Bundrick	August 2	52.0	-1.4
Thomas Holbrook	August 28	55.7	2.3
Michael Lewis-Beck & Charles Tien	August 28	50.1	-3.3
Brad Lockerbie	August 28	58.2	4.8
Andreas Graefe & J. Scott Armstrong	September 3	51.2	-2.2
Mean		52.4	

*These forecasts were reported in the Fall issue of *Foresight*. Three of these were later updated, although in calculating the average error for the group or subgroup only the original forecasts are included. The revised predictions appear in parentheses, as do their release dates and forecast error.

**Obama's share of the two-party vote currently is reported to be 53.4%, although votes are still being counted at the time of this writing.

***Fair updates his forecast quarterly. For the purpose of comparison with other forecasts posted no later than early September, we use Fair's July 31 prediction. His earliest forecast, announced on November 1, 2006, was for Obama to receive 53.5 of the major-party vote, which proved to be only 0.1% in error.

PREVIEW

In the Summer and Fall 2008 issues of *Foresight*, Randall Jones and Alfred Cuzan described 13 regression models used to forecast presidential elections and reported the models' forecasts for the 2008 US presidential election. Here is their audit of the results.

Barack Obama, the Democratic candidate, won with 53.4% of the two-party vote, compared to 46.6% for the Republican John McCain. As shown in Table 1, the models' forecasts of the Obama vote ranged from 47.3% to 55.7%, a wide spread. Moreover, their predictions of the Democratic share tended to err on the low side, with 9 of the 13 being lower than the actual outcome.

Taken as a group, however, the models performed very well. All but one called the election in favor of Obama, and the average of their forecasts was 52.4%, only 1 point off the mark. This result provides further evidence of the value of combining forecasts.

The most accurate individual forecast was generated by Carl Klarner's model, which three months before election day predicted that Obama would garner 53.0% of the two-party vote, an error of less than one-half point.

Alfred G. Cuzán   Randall J. Jones, Jr.

forecaster

Carolyn Allmon, ConAgra Foods

What is your current job?

Senior Demand Planner, Act II Popcorn and David Seeds, Snacks Division, ConAgra Foods. My product lines include microwave popcorn for individual consumers, bulk popcorn for movie theaters, and pumpkin and sunflower seeds.

How did your forecasting career start?

After I received my Master's in Economics, I found a position at the Minnesota Department of Revenue, forecasting tax revenues and refunds and analyzing proposals to levy special taxes, including the "sin" taxes – alcohol, tobacco, gambling. A deciding factor in my hiring was that they appreciated my formal training in time-series analysis. I also took charge of the state's economic model, which gave me a unique opportunity to run policy simulations. One of these dealt with Minnesota's new pari-mutuel betting industry and led to my becoming Director of Pari-mutuels and Finance for the Minnesota Racing Commission.

What attracted you to the forecasting field?

Discovering the predictive power of regression models in graduate school (University of Hawaii). I went to Honolulu because my husband was stationed on Oahu with the Navy. I joined a pilot program for a Master's of Public Economics and Administration. After my first econometrics course, I decided I wanted to forecast.

Were you always a quant?

My undergraduate degree is in math, but I wouldn't call myself that. What drew me to math was the challenge of solving problems. By my sophomore year, I already had almost enough credits for a math major. I also did a second major in history.

What have been your career highlights?

Collaborating with great people in both the public and private sectors, and meeting and sharing ideas with forecasting scholars and practitioners at the ISFs, Forecasting Summits, and the Revenue-Estimating conferences held annually for state revenue forecasters. I've especially enjoyed building and customizing forecasting systems for organizations where statistical models had never been utilized – at the Tennant Company and ConAgra. At Tennant, I represented forecasting on the SAP implementation teams when this ERP was rolled out across the company worldwide.

Reflect on the challenges of being a forecaster.

ERP implementations offer special challenges because the design, development, configuration and testing must be

> Forecasters must be detail oriented, and communicating forecasts to decision makers with the required level of detail is always challenging.

done while concurrently getting out forecasts for on-going business, maintaining data integrity, and adapting the process and tools to the changing organization. Other challenges I've encountered as a forecaster include maintaining objectivity in the face of political pressures, prioritizing forecasting projects, communicating to stakeholders with different perspectives, and securing the support for an effective forecasting process and system.

Forecasters must be detail oriented, and communicating forecasts to decision makers with the required level of detail is always challenging. In the private sector, you have the perennial "Forecast vs. Plan" dilemma and biases toward over- or under-forecasting in the different functional areas. With government, you have those who expect the economic impact of policy changes or new tax proposals to be more or less than you had estimated. Fortunately, I had directors who took those hits for us and who supported our estimates based on our assumptions and methodology.

Tell us about your personal life and interests outside of work.

I'm married to Phil and mom to Pugsy, our furry, blue-eyed Himalayan. I'm a classically trained organist and substitute for regular church organists as time permits. I also teach Sunday school and assist the church treasurer. I enjoy traveling, especially escaping from Minnesota winters to warm climates!

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