

Forecast Disagreement in the Survey of Professional Forecasters

BY KEITH SILL

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any people engaged in activities related to business, financial markets, and policymaking closely follow economic forecasts. Our interest in forecasts stems from the fact that, to an important degree, the decisions we make today are influenced by our expectations about the economy. Accurate forecasts lead to better decision-making and more efficient use of economic resources, and so there is a clear benefit to identifying good forecasts.

An important resource for evaluating the predictions and performance of professional forecasters is the Survey of Professional Forecasters, conducted by the Philadelphia Fed Research Department's Real-Time Data Research Center. The SPF is a quarterly survey that asks a panel of professional forecasters about their projections for a range of economic variables, including output growth, unemployment, inflation, and interest rates. When examining the SPF data, it becomes clear that professional forecasters have wide-ranging views about the future evolution of the economy. This is perhaps a bit surprising, since the statistical methods that underlie good forecasting models are well known, and professional forecasters by and large have access to the same data on the economy's past performance.

With forecasters having similar tools and data to work with, why do

we observe this wide dispersion in their projections?¹ Are expectations wide-ranging because of differences in models and methods used to make the forecasts? Or does the wide disagreement stem from how different forecasters process and analyze information and then use it as an input into their forecast-generation process? To design and implement effective economic policies, it is important to understand how expectations are formed. One way to do so is to study forecast disagreement. In this article we will examine some features of the forecasts that underlie the SPF and discuss what theories and evidence tell us about forecaster behavior and how expectations about the economy are formed and evolve over time.

¹ For a discussion on measuring the accuracy of the survey's forecasts, which is beyond the scope of this article, see Stark (2010).

THE SURVEY'S DESIGN

The SPF is the oldest quarterly survey of macroeconomic forecasts in the United States, having been initiated in 1968 under the leadership of Victor Zarnowitz at the American Statistical Association and the National Bureau of Economic Research. After conducting what was then known as the ASA-NBER Quarterly Economic Outlook Survey for 22 years, the ASA-NBER turned the survey over to the Federal Reserve Bank of Philadelphia in 1990, at which time it was renamed the Survey of Professional Forecasters. The Philadelphia Fed's Real-Time Data Research Center now conducts the SPF. A panel of professional forecasters (there are usually around 45 respondents per survey) is asked to give projections for a range of major macroeconomic variables over various time horizons.²

To maintain high quality, the SPF screens its participants. Most have had advanced training in economic theory and statistics and use statistical models to generate their projections. To keep the integrity of the survey high, participation is limited to those employed by firms or paid by clients to generate forecasts now or in the past. Because of these criteria and the types of individuals who participate in the SPF, we

² The survey results are released to the public free of charge at 10 a.m. on the second or third Friday of the second month of each quarter. The release schedule and the results of current and past surveys, as well as the underlying data, including anonymized individual forecaster projections, are available at <http://philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters>.



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can surmise that fairly sophisticated models and statistical methods underlie their projections.

SPF participants use their models to forecast quarterly values of major macroeconomic variables for up to five quarters, including the current quarter, and annual projections up to three years ahead. In addition, the SPF asks for long-term annual averages for headline and core inflation, real GDP growth, productivity growth, and stock and bond returns. A somewhat unusual feature of the survey is that, instead of asking participants just for single forecasts for output growth, inflation, and the unemployment rate, it asks them to assign probabilities to different outcomes and so gives a more comprehensive picture of the forecasters' views of the future.³

SPF FORECAST DISAGREEMENT

For the most part, the main, or "headline," forecast numbers reported in the SPF are the median values across forecasters. Each median, though, belies the variation that exists among individual projections for key variables that describe the macroeconomy. In fact, the range of forecast values underlying the median can be substantial, and it changes over time. At times, the forecasters show more agreement and at other times more disagreement in their projections.

The Real-Time Data Research Center website provides data on SPF forecast disagreement for the variables that are regularly reported in the SPF. The measure of disagreement that is reported is the difference between the 75th percentile and the 25th percentile of the forecasts, which is called the interquartile range. In other words,

³ See my 2012 article for more on forecast uncertainty and the forecast probabilities that are reported in the SPF. That article also presents some evidence on how forecast disagreement affects the macroeconomy.

suppose there are 100 separate forecasts for annual real GDP growth in 2014. Order the forecasts from highest value to lowest value, and take the difference between the 75th slot and the 25th slot as the measure of disagreement. We measure disagreement in this way in order to ensure that any outliers among the forecasts, perhaps due to mistaken entries in the respondent questionnaires, do not unduly influence the measure of disagreement. Figures 1 through 3 show plots of disagreement measured by the interquartile range from the center's website for real GDP growth, GDP price index inflation, and the unemployment rate. Each measure of disagreement is for the four-quarters-ahead forecast as of the date on the horizontal axis.

The range of forecast values underlying the median can be substantial, and it changes over time.

The charts show that disagreement generally tended to be higher in the survey's early years — the late 1970s and early 1980s — compared with the latter half of the sample. Broadly speaking, this pattern of declining disagreement tracks the period known as the Great Moderation from 1984 to 2008, when the overall volatility of the economic data was lower than in the pre-1984 period.⁴

How do we interpret the data in Figures 1 through 3? Take the case of disagreement for real GDP growth. Since the early 1990s, the disagreement for forecasts of real GDP growth four quarters ahead has bounced around in a range of 0.5 percentage point to 1.5 percentage points, with an average of 0.86 percentage point.

⁴ For more on the Great Moderation, see my 2004 article, "What Accounts for the Postwar Decline in Economic Volatility?"

Roughly speaking, this suggests that about 50 percent of the forecasts fall within a range of about 0.4 percentage point below to about 0.4 percentage point above the median forecast. The other 50 percent of the forecasts are even further away from the median. Consequently, the disagreement among the forecasters seems not too large but nonetheless represents a significant difference between the top and bottom of the distribution. By way of comparison, the standard deviation of quarterly real GDP growth from the first quarter of 1991 to the third quarter of 2013 was about 2.5 percentage points at an annual rate.

Recall, though, that the measure of disagreement shown in Figures 1 through 3 is somewhat conservative.

To calculate it, we make no use of the forecasts in the top and bottom 25 percent of the distribution — which, if included, would widen the disagreement. Indeed, this potentially wide disagreement is part of the reason that the SPF generally reports median rather than average forecasts. The median is the midmost forecast when forecasts are ranked from high to low. So, unlike with the average forecast, the effect of outliers is discounted.

If we use all the forecasts to calculate the standard deviation across projections of four-quarters-ahead real GDP growth, we obtain Figure 4. For the most part, the standard deviation measure tracks the interquartile range measure fairly closely, though it is clearly more volatile, especially early in the sample. This volatility may partly reflect reporting errors by members of the forecast panel. Sometimes an SPF respondent will submit

FIGURES 1–3

Significant Dispersion for Key Indicators

Figure 1: Real GDP Growth Rate Dispersion by Quarter

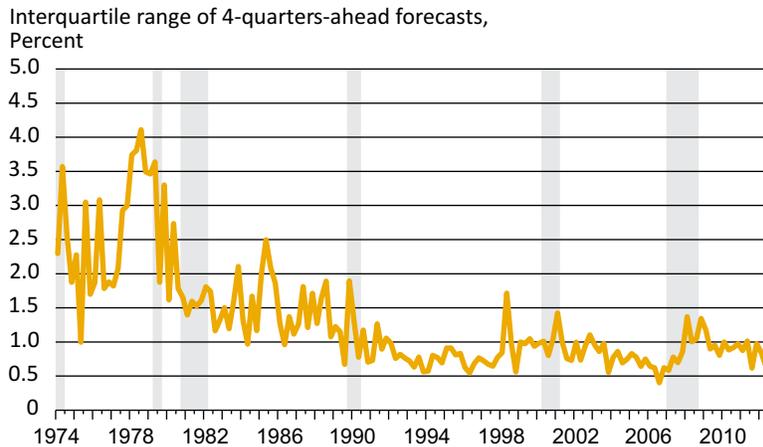


Figure 2: Unemployment Rate Dispersion by Quarter

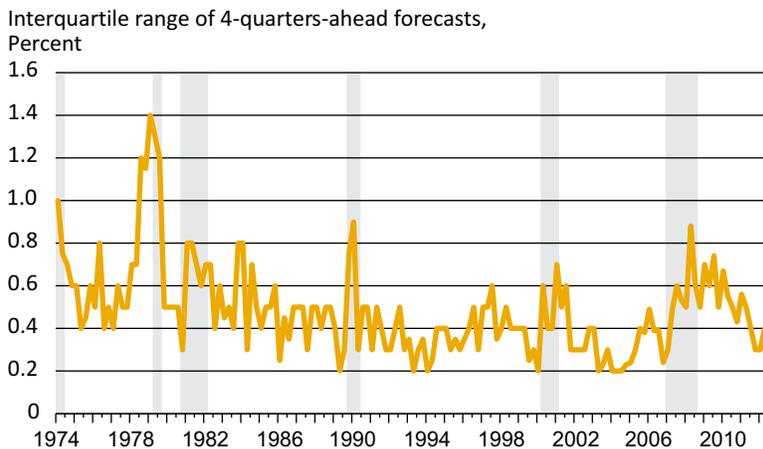
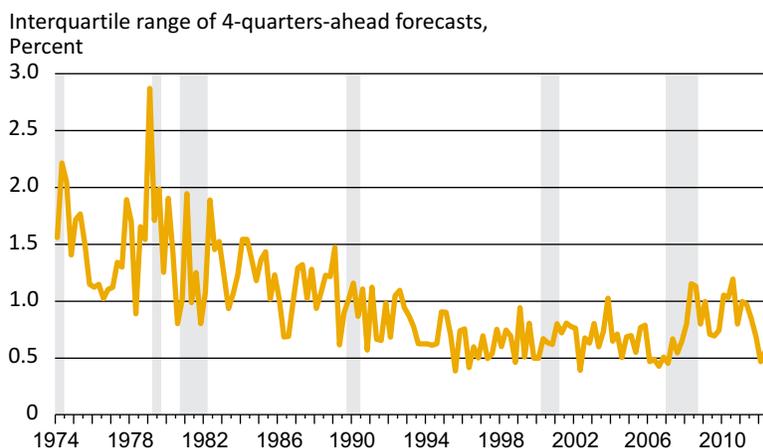


Figure 3: GDP Deflator Inflation Rate Dispersion by Quarter



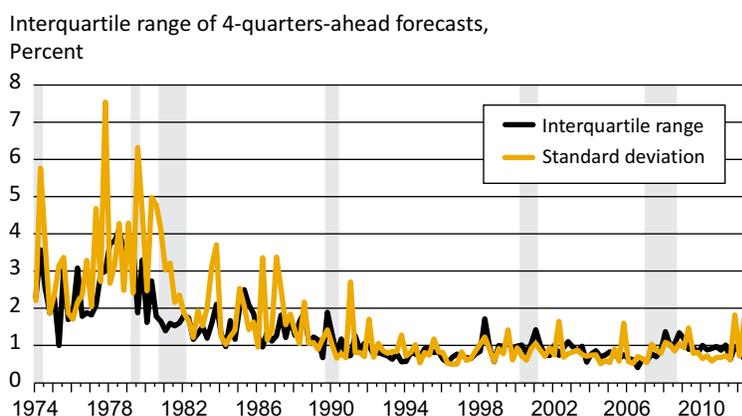
Source: Survey of Professional Forecasters, Federal Reserve Bank of Philadelphia.

a forecast that seems extreme relative to those of the other respondents. If the outlier appears to be an error, that forecast is removed. In general, though, it is difficult to identify reporting errors versus actual views. For example, in the survey for the first quarter of 2013, the interquartile range for the four-quarters-ahead real GDP growth projections is 0.6, while the standard deviation is 1.7. However, one forecaster had entered a four-quarters-ahead real GDP growth forecast of 12.6 percent — which might have been a reporting error. If we exclude that forecast, the standard deviation falls to 0.832, which is much closer to the interquartile range. The median and the interquartile range are less affected by such outliers.

We can see this in Figure 5, which plots the forecasts for four-quarters-ahead real GDP growth from the SPF for the first quarter of 2013. The gold dots are observations in the upper 25 percent and lower 25 percent tails of the distribution. We see two outliers, one calling for 12.6 percent growth and one calling for a 1.5 percent contraction. We cannot say for sure that these were reporting errors, but it seems possible. Excluding those two, the remainder fall in a range of about 2 percent to 4.2 percent, while the central tendency ranges from 2.5 percent to 3.1 percent.

Disagreement still significant. If we use all the forecasts to calculate the standard deviation, we can construct confidence intervals for the forecasters. A confidence interval indicates the probability of a forecast falling within a certain range. Typically, a 95 percent confidence interval is plus or minus two standard deviations around the mean estimate.⁵ In the case of forecasts for real GDP growth four quarters

⁵ This is the case if the observations are drawn from a normal distribution.

FIGURE 4**Standard Deviation Generally Tracks GDP Forecast Range**

Sources: Survey of Professional Forecasters, Federal Reserve Bank of Philadelphia; author's calculations.

ahead, this calculation suggests that we can estimate that 95 percent of the forecasts will, on average, be in a range of about 1.7 percentage points above to 1.7 percentage points below the mean of the forecasts (the average standard deviation of the four-quarters-ahead projections from the first quarter of 1992 to the first quarter of 2013 is 0.85). So, if the average forecast was 3 percent, we would estimate that 95 percent of the forecasts for four-quarters-ahead real GDP growth would fall in a range of about 1.3 percent to 4.7 percent. This range highlights that the SPF forecasters typically have fairly divergent views on how real output growth is likely to evolve in the not-too-distant future.

When looking at the interquartile ranges of the forecasts for the unemployment rate and GDP deflator inflation, we also see a tendency toward a decline in average disagreement in the post-1990 sample. As it had for real GDP growth, disagreement among these forecasts increased following the

recession that began in December 2007. Disagreement for the unemployment rate forecast is a bit lower than that for inflation or output growth, possibly because the high persistence in the unemployment rate makes it a somewhat easier variable to forecast. Nevertheless, the range of views on future unemployment rates is significant. Take the results of the survey taken in the first quarter of 2013. Figure 6 plots the forecasts for the four-quarters-ahead unemployment rate from high to low. The gold dots again denote the upper and lower quartiles of the distribution. We see that while the interquartile range was fairly small at around 0.5, the range of overall forecasts was larger. Some forecasters thought that the economy would make little if any progress on the unemployment rate (the median current-quarter forecast for the 2013 first quarter unemployment rate was 7.8 percent). But some thought unemployment would fall below 7 percent. Most thought it would be in a range of 7.3 percent to 7.6 percent.

Figure 7 shows the forecasts for GDP deflator inflation from the 2013 first quarter SPF. Again, two look suspicious — both calling for significant deflation — and would have a large impact on the standard deviation of the forecasts. Excluding the deflation outliers, the forecasts range from about 1.3 percent for inflation four quarters ahead to almost 4 percent. The central tendency is narrow at 1.7 percent to 2.3 percent. But we again see that professional forecasters can have strikingly different views about how the economy will evolve over the next 12 months.

DIFFERENT MODELS AND METHODS

The forecasters who make up the SPF panel use a variety of statistical models to help them make their projections, and this variety of models surely plays a role in forecast disagreement. But how large a role might that be? Their models generally fall into one of two major categories: reduced-form models and structural models. Reduced-form models impose little, if any, economic theory to refine their structure. For example, one of the simplest forecasting models for real GDP growth is to suppose that current GDP growth is related to past GDP growth in a linear fashion. To forecast a greater range of variables, the model can be expanded by adding more lagged variables to form a system of equations that relates current values of variables such as output growth, inflation, and interest rates to their lagged values. A forecaster using such a system of equations chooses which variables to have in the system as well as the number of lags of variables to use. Once those choices are made, the model can be estimated using historical data and then used to generate forecasts. One does not need to bring much economic theory to bear when specifying such a reduced-form model, since there are typically no restrictions on the esti-

FIGURES 5–7

Strikingly Different Year-Ahead Projections

Figure 5: Real GDP Growth Rate Forecasts

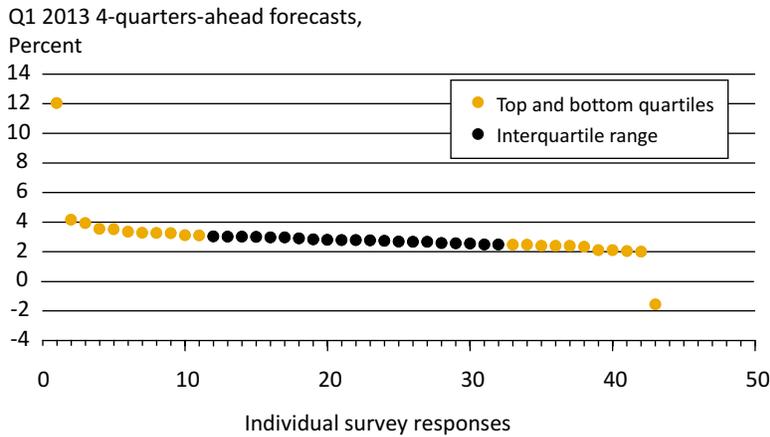


Figure 6: Unemployment Rate Forecasts

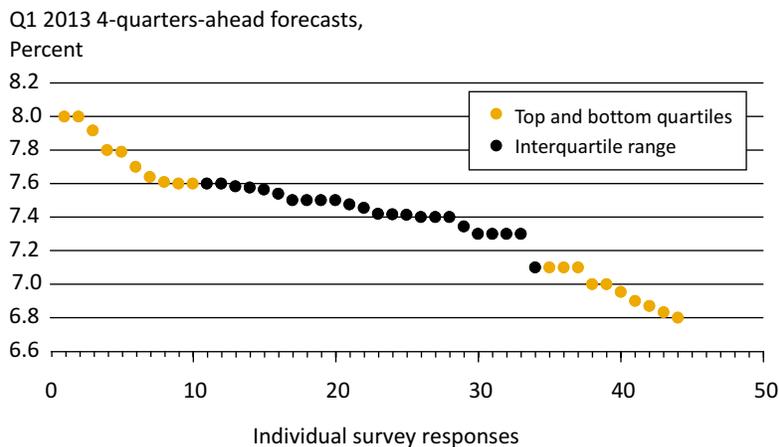
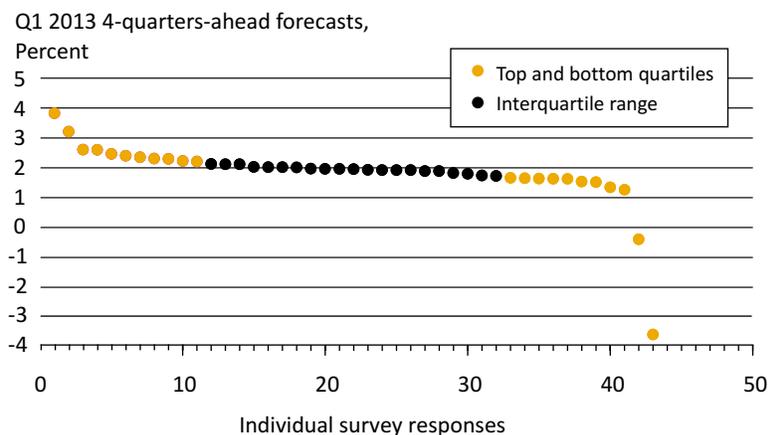


Figure 7: GDP Deflator Inflation Rate Forecasts



Source: Survey of Professional Forecasters, Federal Reserve Bank of Philadelphia.

mated coefficients and no restrictions on how the model's variables interact with each other.

Another approach to building a forecast model is to use economic theory to restrict the way in which the variables interact. For example, one might stipulate that the relationship between household consumption and hours worked in the labor market is related to the real wage in some particular way, or that the relationship between current and future consumption is tied in a specific way to the interest rate. Models that impose economic theory on the data's interrelationships are called structural models. Like reduced-form models, structural models relate values of variables to their lagged values. But structural models use economic theory to impose complex relationships among those variables. Structural models are especially useful for honing the story behind the forecast. For example, such models may indicate that output growth will rise because of higher demand today, or that inflation is expected to fall because firms expect the marginal costs of production to fall in the future. These kinds of stories that are consistent with economic theory are typically more difficult to tease out when using reduced-form models.

There is another element that usually is an important part of the forecast process: judgment. Often forecasters will examine the historical errors in the equations of their models — that is, how much the predicted value from the equation differed from that actual value in the data. If the forecast is persistently missing on the high or low side, the forecaster may alter the equation away from the estimated values a bit so that its predictions are more in line with the most recent data observations. This is a judgment-based adjustment of the forecast whereby forecasters subjectively alter the predictions generated by the statistical model to

bring them more into conformity with the recent behavior of the economy and their own views on how the future is likely to unfold. Typically, data, models, and judgment are combined to produce the final forecast.

If forecasters are using different models on which to base their forecasts, then we might expect to see disagreement in those forecasts. Some models might be more accurate descriptions of the economy than others. If one forecasting methodology is consistently better than another and the data are able to discriminate among the models, we should see bad models being driven out over time by good models. Likewise, we should see that forecasters using the best models should consistently produce better forecasts than other forecasters do. That is, if model heterogeneity is the most important reason that forecasts differ and the data are informative about the models, then we should be able to identify forecasters and models that reliably outperform their peers.

Evidence casts doubt. However, some evidence from the forecast evaluation literature casts some doubt that model heterogeneity is the key element behind forecast disagreement. First, one of the most robust findings from the forecasting literature is that mean forecasts systematically outperform individual forecasts. That is to say that over time, a more accurate forecast can be had by taking the average of many different forecasts rather than sticking with one individual forecaster's projections. If one forecaster and his or her model were consistently producing better forecasts, then we wouldn't expect to see such a gain from averaging.⁶

Why does this forecast averaging tend to work so well compared with any one forecast over time? If there was one, known, true model of

the economy, then the forecasts from that model would dominate alternative models. But we don't have the true model of the economy. Yet, because the economy is so complex, different models may capture different features of the economy in a successful way. At certain times, some of those features may be more important for successful forecasts than at other times. So by averaging a wide range of forecasts, we can incorporate many features of the economy that are impossible to capture

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Aside from forecast averaging, is there other evidence that suggests model differences may not be the key factor underlying forecast dispersion? Models can differ in how they incorporate economic shocks, which are defined as unpredictable disturbances to the economy from events such as the outbreak of war or an unexpected surge in global commodity prices. For example, some models might be better at predicting how the economy will respond to oil price shocks, while other models might be good at predicting how the economy will respond to fiscal policy shocks. Therefore, depending on the specific mix of shocks hitting the economy at any one time, some models may produce the most accurate forecasts for one period, only to have their relative predictive power reversed when a different set of shocks hits. However, shocks and their effects tend to persist. That is, the impact tends to decline slowly as the shocks fully work their way through the economy. This persistence implies that models that are especially accurate for particular

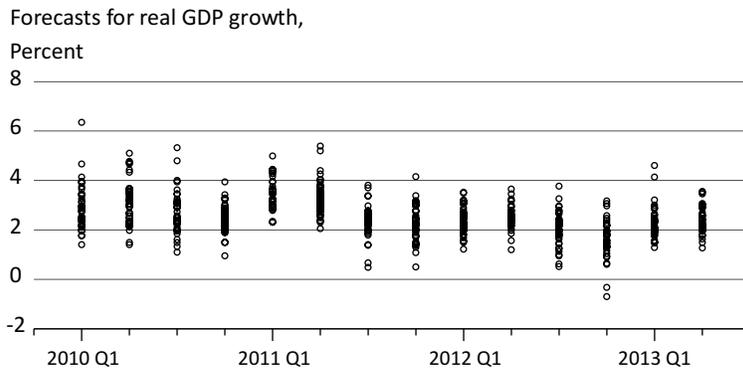
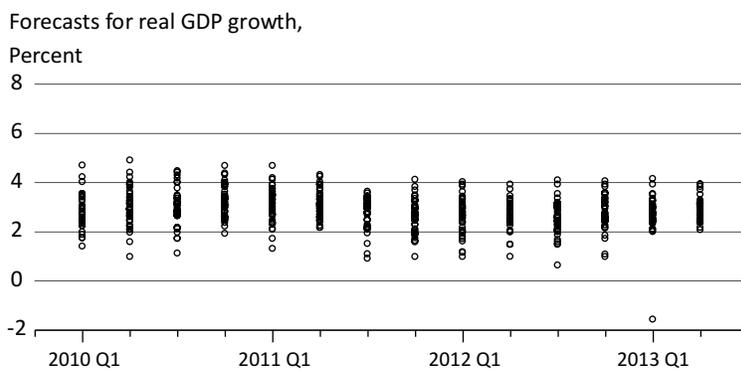
shocks should generate persistently better forecasts as long as the shocks a particular model is good at analyzing are still important drivers of the dynamics of the economy. We might then expect that some forecasters will give more accurate forecasts for several reporting periods in a row. However, another finding from the empirical forecasting literature is that the best forecaster in any one period is no more likely to be the best in the next period.⁷ So, although economic shocks are per-

sistent, forecast performance is not.

The findings that average forecasts tend to outperform individual forecasts and that top forecasters don't stay on top for long suggest that differences in models may not be the most important element behind forecast disagreement. But as is often true in economics, the case is not so clear-cut. Recent research by Andrew Patton and Allan Timmermann examines how forecast disagreement changes with the forecast horizon. Using survey data from Consensus Economics, they find greater disagreement among longer-term forecasts than near-term forecasts. Because variables such as real GDP growth and inflation tend to return to their mean values over time, the observation that long-horizon forecasts show more disagreement is consistent with the idea that differences in economic models are an important factor. This is because different models might be calibrated to yield different long-run averages for key variables, and model-based long-run forecasts will

⁶ See the 2006 article and references therein by Allan Timmermann.

⁷ See the 2007 article by Michael Bryan and Linsey Molloy.

FIGURE 8**No Wider Variation in Longer-Term Forecasts****Range of 1-Quarter-Ahead GDP Forecasts****Range of 4-Quarters-Ahead Forecasts**

Source: Survey of Professional Forecasters, Federal Reserve Bank of Philadelphia.

Note: In the upper chart, one outlier forecast from the 2012Q3 survey was eliminated. In the lower chart, one outlier from each of the following surveys was eliminated: 2010Q1, 2012Q3, and 2013Q1.

reflect those differences.

This pattern is more difficult to discern in recent SPF projections for real GDP growth. However, the longest forecasts we can use from the SPF are looking only four quarters ahead from the quarter in which the survey is conducted, which is more in the realm of near-term forecasts. With that caveat, Figure 8 plots individual forecasts of one-quarter-ahead and four-quarters-ahead real GDP growth from the first quarter of 2010 to the second quarter of 2013. Looking at the panels in the

figure, there is no clear tendency for the longer-horizon forecasts to show more disagreement than the shorter-horizon forecasts over this period.⁸ If we were to extend the data sample back to 1970, we would see the same basic pattern: There is no obvious increase in disagreement when we move from one-

⁸ Patton and Timmermann were able to compare forecast horizons as short as one month with those as long as 24 months. In addition, they used the Consensus Forecast survey for 1991 to 2008, which typically had about 25 forecasters in the panel.

quarter-ahead to four-quarters-ahead real GDP forecasts in the SPF.

In considering how near-term forecasts might differ from long-term forecasts, it is important to note that near-term forecast disagreement is more likely to be influenced by current information that is used to kick off the forecast. As noted earlier, a forecast combines models with data and judgment to generate a projection. The timeliness of the data that a forecaster has in hand when making a forecast and the extent to which the forecaster discerns the true state of the economy from that data are critical elements when projecting the economy's future state. Perhaps the data and information analysis that go into forecasts are also key drivers of forecast disagreement.⁹

AN IMPERFECT SIGNAL

As new data become available and are put into the forecasting models, the projections are modified, sometimes dramatically. So how forecasters respond to the arrival of new information is an important factor in the forecast-generation process. When constructing models of the economy, economists often assume for simplicity's sake that people costlessly receive all the information they need to make their decisions. In reality, though, information is costly to process and often subject to revision over time. Take the release of quarterly real GDP data. An initial estimate is released in the month after the end of the quarter, a second release two months after the end of the quarter, and a final release three months after the end of the quarter. But even that's not really the "final" release, since the estimate will again be revised in July for the next several years, and then again every five years or so with benchmark revisions

⁹ Note, though, that without some discipline, models with heterogeneous forecasting rules can rationalize any disagreement outcome.

to the national income and product accounts.¹⁰ Forecasters looking at today's data to put into their models realize that they have only an imperfect signal of the true state of the economy at any point in time. In contrast to the case of full information, we can say that there are information “frictions” that make the true state of the economy difficult and costly to assess.

There are two prominent theories of imperfect information in macroeconomics that have different implications for what we should observe in forecast surveys such as the SPF. The first, often referred to as the sticky-information theory, is described in a 2002 paper by Greg Mankiw and Ricardo Reis. In this theory, economic agents such as forecasters are assumed to update the information they use to make decisions and forecasts randomly — with a certain probability each period that is independent of economic conditions or past decisions. It is as if each day people play an information lottery. If they win the lottery, they go ahead and update their view of the world based on current data. And the assumption is that they receive full information about the state of the economy when they update. If they lose, they don't update their information and continue to make decisions and forecasts based on stale data.

Clearly, this is an extreme view of the world and is unlikely to be strictly true. But if there is a fixed cost to acquiring and processing new information, then households and firms

will update their information only infrequently.¹¹

Another prominent theory of information frictions assumes instead that agents monitor the flow of data and update their information continually, but that the information they receive about economic fundamentals is contaminated by random “noise” that obscures the signals they are interested in. For example, take the case of a monetary policymaker who is concerned about the behavior of inflation when setting interest rates. At a point in time, the policymaker has observations on current and past inflation and tries to discern the trend in inflation from transitory movements that are likely to dissipate over time. Inflation may be higher today because of, say, a temporary weather shock that affects food prices. The policymaker is more likely concerned with the underlying trend rate of inflation but must make some inference about that unobserved trend from the underlying data. So, he or she doesn't necessarily possess the full information. More generally, time and resources must be spent to best estimate the desired information, and because time and resources are costly, there are tradeoffs in deciding how to process information.

Information frictions have implications for forecast behavior, including forecast disagreement. How do forecasters respond to economic shocks when there are information rigidities? In the case of sticky information, not all forecasters are updating their projections in response to the shock at the same time.¹² Since the respondents are surveyed at the same time, we would hypothesize that the average forecast

will be somewhat inertial and slow to adjust to the shock. Consequently, forecast errors will persistently be above or below zero (depending on whether the shock is positive or negative) for some time, though eventually everyone updates his or her information and the average forecast error returns to zero.¹³

Similarly, in the case of imperfect information, the change in the average forecast in response to the shock is inertial — in this case only a fraction of the signal about economic fundamentals is incorporated into the current estimate of the underlying state of the economy so that adjustment to the data is only partial. This slow response is reflected in the persistence of forecasters' beliefs about the underlying state of the economy, which in turn leads to a somewhat inertial adjustment of the forecasts to shocks to economic fundamentals.

Effect of shocks on disagreement. So, both imperfect information theories suggest that forecast errors might be persistently below or above zero in response to shocks (but that the errors converge to zero over time). But what about forecast disagreement? Here, the two theories offer different predictions. The sticky-information theory predicts that disagreement will rise in response to shocks. This happens because not all forecasters are updating their information sets and forecasts after a shock, so the forecasts of those who do update may move further away from the forecasts of those who don't: Disagreement increases. The noisy-information theory predicts that disagreement should not respond to shocks. In this theory, forecasters con-

forecasts largely for internal use might update those forecasts less frequently than would a forecaster who primarily sells forecasts to a wide clientele.

¹³ Key references for the macroeconomic implications of imperfect information literature include Lucas (1972), Sims (2003), and Woodford (2003).

¹⁰ The most recent benchmark revisions were conducted in the summer of 2013. According to the Bureau of Economic Analysis, comprehensive revisions encompass (1) updated definitions and classifications to more accurately portray the evolving U.S. economy, (2) changes in presentations to make the NIPA tables more informative, and (3) statistical changes that introduce improved methodologies and newly available and revised source data. See <http://www.bea.gov/newsreleases/national/gdp/gdpnewsrelease.htm>.

¹¹ That the presence of fixed costs of updating information can rationalize the sticky-information model is derived in a 2006 article by Ricardo Reis.

¹² It is plausible, for instance, that an economist employed by a bank or other firm to generate

tinually monitor and react to the flow of data.¹⁴ The idea is easier to grasp if we assume that forecasters are using the same model. Then, if they are also monitoring the data continually, the disagreement among forecasts arises from idiosyncratic differences in how the forecasters process the information that ends up being fed into their models. For example, suppose the data for the model include the real interest rate, which is not observed directly but must instead be inferred by subtracting the expected rate of inflation from the nominal interest rate. Depending on how they measure expected inflation, different forecasters can arrive at different measures of the real interest rate. As long as the ways that individual forecasters process information do not themselves respond to shocks, then the dispersion of the forecasts will not vary in response to shocks.

To sum up then, both imperfect-information theories predict that forecast errors should show some persistence, but they have different implications for forecast disagreement. The sticky-information theory suggests that disagreement rises in response to shocks, while the noisy-information theory suggests that it doesn't.¹⁵

IS THERE EMPIRICAL EVIDENCE?

Is there empirical evidence on the role of imperfect information in forecaster behavior? Recent work by Olivier Coibion and Yuriy Gorodnichenko examines whether the implications

¹⁴ This assumes that the dispersion of the idiosyncratic noise shocks that forecasters receive does not respond to economic fundamentals such as inflation or output. However, if forecasters who receive the same signal interpret it differently, then forecast dispersion can be correlated with economic shocks. See Coibion and Gorodnichenko (2012) for details.

¹⁵ The two theories have additional predictions for the data besides those we have discussed here. See the 2012 paper by Coibion and Gorodnichenko for a fuller exposition.

of imperfect-information theories are found in the forecast data. They use a variety of surveys, including the SPF, to investigate how forecast errors and disagreement respond to shocks and whether that response can be rationalized by imperfect-information theories.

Assessing the response of economic variables to shocks can be tricky because shocks themselves are often unobserved and so have to be

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identified from the data. Coibion and Gorodnichenko identify several shocks, including monetary policy shocks, total factor productivity (TFP) shocks, oil shocks, and fiscal policy shocks, and then use regression methods to see how inflation forecast errors and forecast disagreement respond to these shocks.¹⁶ For the most part, the forecast horizon under investigation is one year ahead.

Recall that one key prediction of the imperfect information theories is that forecast errors should show some persistence in response to shocks. If a shock hits the economy and forecasters either don't incorporate it quickly into their forecasts or else have a hard time extracting the relevant signals from the data, then their forecasts are likely to over- or under-shoot until these

¹⁶ Total factor productivity is the residual in accounting for economic output after the contributions of labor and capital inputs have been measured. It can be viewed as the contribution of technological change to output growth. A monetary policy shock can be thought of as the surprise component of the monetary policy instrument. It is the difference between a realized policy outcome — usually a short-term interest rate — and the rate that had been predicted by a specific model.

information problems are resolved. Indeed, Coibion and Gorodnichenko generally find serially correlated forecast errors in response to a variety of shocks, especially TFP and oil price shocks. For example, after an inflationary shock, they find a predictable sequence of serially correlated positive inflation forecast errors. Over time, though, these errors converge back to zero — just as the theory predicts

they should. If there were no information problems confronting forecasters, we would expect that forecast errors would in turn not show predictable patterns in the data.

Coibion and Gorodnichenko also examine how forecast disagreement responds to shocks. Recall that this response has the potential to distinguish between the sticky-information and noisy-information theories. After examining how disagreement changes in response to many different shocks that hit the economy over the past 30 years or so, they conclude that, on balance, structural shocks do not seem to notably increase disagreement across forecasters. This finding gives an edge to the noisy-information theory, though for other dimensions of the data, the sticky-information theory does better.¹⁷

¹⁷ Some of Coibion and Gorodnichenko's findings, though, are more consistent with the sticky-information theory. For example, the convergence rate of forecast errors is just as rapid for monetary policy shocks as it is for TFP shocks. Under the noisy-information theory, if TFP shocks were more important for determining productivity and economic growth, one might expect forecasters to pay more attention to these shocks, which implies that forecast error convergence would differ among shocks.

It seems that elements of both theories are present in the data.

This evidence indicates that imperfect-information theories are consistent with the forecast data, though discriminating between the two theories is difficult. Is imperfect information important or insignificant in the data? Coibion and Gorodnichenko also try to answer this question using data from the SPF on inflation forecasts. In the context of the sticky-information model, their estimates imply an average duration of six to seven months between information updates on the part of forecasters.¹⁸ In the context

of imperfect-information models, the estimates imply that new information receives less than half the weight it would if there was no imperfect information and forecasters did not have to extract the relevant signals. Thus, the evidence is consistent with imperfect information having a significant role in how forecasters process new information and how often they acquire it.

¹⁸ It seems puzzling that professional forecasters would update their forecasts infrequently, but other researchers have also found patterns in the data consistent with this implication. Two such studies are Clements (2012) and Andrade and Le Bihan (2010).

CONCLUSION

Forecast disagreement is large and varies over time. Differences in how forecasters see the economy evolving in the future can be attributed to the models they use and the way they monitor and incorporate into their forecasts the heavy, continual flow of information on the state of the economy. Empirical evidence from forecast surveys suggests that both model heterogeneity and imperfect information about the economy play roles in the wide dispersion in professional forecasts. 

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