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17 Consensus and Uncertainty in Economic Prediction

17.1 Concepts and Problems

Although all forecasts are by their very nature probabilistic statements, most economic predictions quote but a single value to be assumed by a certain variable, without specifying the attached probabilities. Often many such point forecasts are available for a given target variable from a business outlook survey. If they show a high degree of agreement, does this indicate that the forecasters confidently expect the outcome they commonly predict to come true? More generally, does the dispersion of the point forecasts reflect their authors' uncertainty (i.e., their relative *lack* of confidence)? This paper deals with these and other related questions, drawing on a set of data that is very rare in economics in that it includes related point and probabilistic forecasts from the same sources.

17.1.1 Consensus

Averages from economic outlook surveys are frequently called "consensus" forecasts or treated as such. The term has entered the popular discourse without having been defined in a generally accepted way. But it is clear that the degree to which a survey average is representative of the collected individual predictions can vary greatly depending on the nature of the underlying distribution. There may be no meaningful consensus if the distribution of the point

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forecasts in question is highly diffuse or multimodal because of large differences among the underlying models. On the other hand, a consensus would be strongly in evidence for any unimodal, symmetrical, and sufficiently tight distribution (see Schnader and Stekler 1979). The inverse aspect of the consensus is the dispersion of a sample of point forecasts, which can be measured simply by their standard deviation.

In predicting the value an aggregate variable is to assume in a given period, individuals and groups use in part the same public information and the same established techniques and relationships. The common elements induce some positive correlation across the resulting forecasts. Insofar as the makers and users of the forecasts interact and influence each other, directly or indirectly, the correlation of corresponding expectations would be reinforced. That such interdependencies may be substantial is suggested by the existence of informal exchanges and organized polls of opinion, market arrangements for the sale of expert advice, and media dissemination of public forecasts. A frequently encountered surmise is that many forecasters are risk averters who do not wish to deviate much at any time from the views of the future that appear to be prevalent. If so, the distribution of the approximately contemporaneous point forecasts for a given target would be further tightened around an influential "consensus" value.

But there are also important limitations and countertendencies to this process. Only the hypothetical expectations containing all the pertinent information generated in the economy are necessarily self-fulfilling; actual forecasts, even if widely shared, are not since they are inevitably based on partial and imperfect knowledge. No mechanism has been discovered to ensure the convergence of the forecasts to a unique and stable equilibrium path. Attempts to predict average opinion or what others are likely to predict that average to be and so forth run into the frustrating "infinite regress" problem. Certainly, genuine predictions intended to guide the decision making or affect views in the marketplace do not merely mimic one another. Thus simple averages of forecasts from successive business outlook surveys have proved to be more accurate over time, and also less biased, than most of the corresponding forecast sets of the individual participants. Evidently there is a good deal of independent information in the individual forecast series so that their collinearity is limited, and combining them yields net gains in predictive power (Zarnowitz 1967, pp. 123–26; 1984a; 1985a).[1]

17.1.2 Uncertainty

In a number of recent studies, which are cited below, high (low) dispersion of predicted price changes across survey respondents is interpreted as being

1. On methods to choose a diversified "portfolio" of forecasts and weights that reduce the variance of the resulting composite, see Bates and Granger 1969 and Newbold and Granger 1974. On the conditions under which unweighted aggregate predictions are optimal or nearly optimal, see Einhorn and Hogarth 1975 and Hogarth 1978.

indicative of high (low) "inflation uncertainty." Thus uncertainty is here simply identified with the inverse of what was labeled "consensus" in the preceding subsection.

It is important to recognize that this approach does not involve any direct measurement of uncertainty in the usual sense of that term. The latter is a function of the distribution of the probabilities that a forecaster attaches to the different possible outcomes (values) of the predicted event (variable). The tighter this distribution, the lower is the associated uncertainty.

For an informed outside assessment of uncertainty so defined, therefore, some sufficient knowledge of the probabilities involved would seem necessary. Inferences from point forecasts do not produce such knowledge; they may or may not provide helpful clues in its absence. When the standard deviation of a set of corresponding predictions by different individuals is taken to indicate uncertainty, the underlying assumption is that this interpersonal dispersion measure is an acceptable proxy for the dispersion of intrapersonal predictive probabilities or beliefs held by the same individuals. The validity of this assumption can by no means be taken for granted; it is an empirical question that is best answered by direct measurement and testing.

Some events do have stable and known distributions of outcomes; others do not. It is generally easier to predict stationary than nonstationary variables, transitory than permanent changes, smooth trends than abrupt turning points. The stabler and more knowable the underlying "objective" probability distributions are, the greater presumably is the accuracy of the forecasts and the confidence with which the subjective probabilities of the predicted outcomes are held. The concept of uncertainty adopted here applies in principle to any probabilistic forecast, whether held with a high or a low degree of confidence.[2]

Simple schematic diagrams suffice to show the important distinction between consensus and uncertainty and how the two may be related. In figure 17.1 the point forecasts reported by the individuals A, B, and C are viewed as the expected values of their respective probability distributions. The degree of *consensus* among the three (or any number of) survey respondents is said to be "high" when their point forecasts are clustered, "low" when they are widely dispersed. The degree of *uncertainty* is said to be high when the predictive distributions of A, B, C, . . . are diffuse, low when they are tight. As illustrated in panels *a* and *b* of the figure, high consensus may be associated with either low or high uncertainty. Similarly, low consensus may be associated with either low or high uncertainty (panels *c* and *d*).

Suppose, however, that both uncertainty and consensus depend on the accuracy record of the recent point forecasts. The better that record, the tighter

2. Thus no use is made in this paper of the distinction between "risk" and "uncertainty" (Knight 1921; Keynes 1936), which has important implications in other contexts (chapter 2; Meltzer 1982).

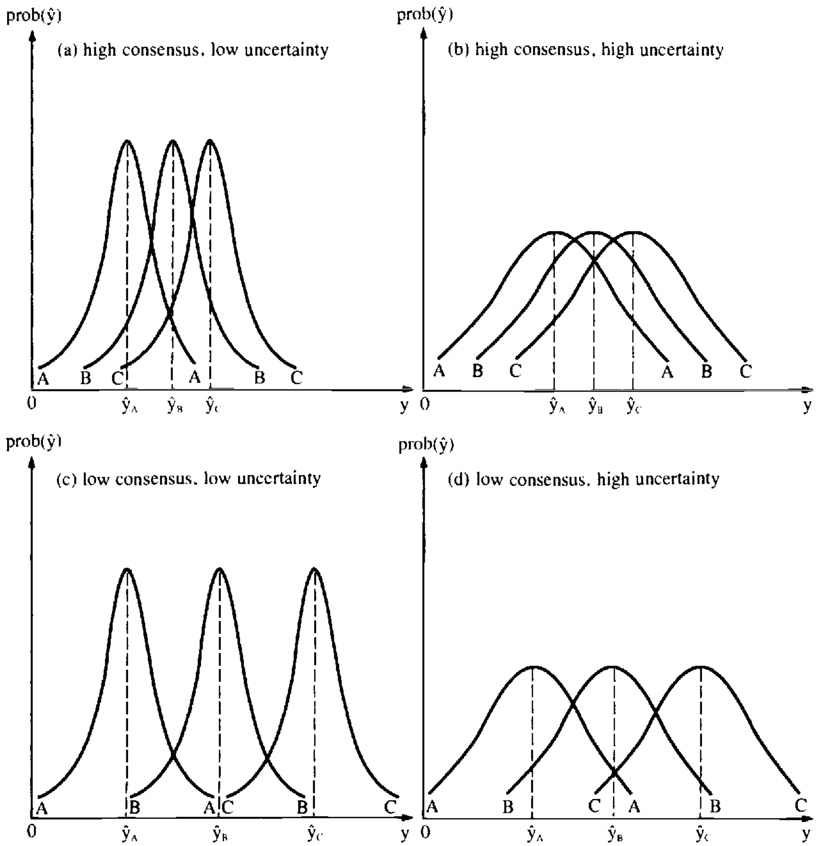


Fig. 17.1 Examples of contrasting combinations of consensus and uncertainty
Note: Curves A, B, and C represent the probability distributions of alternative forecasts from sources A, B, and C, respectively. The probabilities prob(y) are measured vertically; the different values of the predicted variable (y) are measured horizontally. The point forecasts are y_i, (i = A, B, C, . . .).

will be the individuals' predictive probability distributions and the smaller will be the differences among their new point forecasts. In other words, forecasting successes should be associated with high consensus and low uncertainty; forecasting failures, with low consensus and high uncertainty. If so, then the combinations *a* and *d* in figure 17.1 would have higher probabilities of occurrence than the opposite combinations *b* and *c*.

Bomberger and Frazer (1981) tested the relationship between the dispersion of the individual forecasts of inflation (σ_t) and a weighted average of past errors in these forecasts ($\sqrt{S_t}$), using data from a semiannual survey of economic forecasters conducted by Joseph A. Livingston, a syndicated financial columnist.[3] They found a high positive correlation ($r^2 = .77$) between the two measures, which they argued supports the use of σ_t as a proxy for inflation uncertainty. However, this result, though suggestive, is inconclusive. Past forecast errors represent only one of the presumptive determinants of uncertainty; others, more future-oriented, are at least as important. They include the latest readings on the various influential indicators, the recent trends and prospective shifts in economic policies, and changes in the external factors affecting business and finance. Each of these is a source of signals that often diverge and are subject to different interpretations, and hence of uncertainty.

There is also a statistical problem here: the serial correlation of errors from the Livingston survey predictions could well account for much of the association between σ_t and $\sqrt{S_t}$. The predominant finding from a number of studies of inflation forecasts is that they generally fail the conventional tests of unbiasedness, efficiency, or consistency.[4]

17.1.3 Hypotheses and Tests

For any time series, increased volatility tends to be associated with decreased predictability. Thus the more variable inflation is, the less of it will be anticipated. But when inflation rises to unusually high levels, it is likely to become more volatile. Repeated policy attempts (*a*) to keep unemployment low by stimulating spending and (*b*) to counter the resulting intermittent bursts of inflation inevitably produce monetary instability. People increasingly realize how this process works, and so anticipated inflation will rise and become more variable, augmenting uncertainty.

Extensions of this hypothesis attribute adverse real effects to such developments. High and volatile inflation raises frictions in the markets and lowers productivity. Prior contracts delay adjustments toward shorter commitments and more indexation. The effectiveness of relative prices in guiding and coordinating economic actions is impaired as distinguishing signals from noise in the observed absolute prices becomes increasingly difficult. These arguments have been used in attempts to explain positive comovements of inflation and

3. Livingston's June and December columns, published in the *Philadelphia Bulletin* and the *Philadelphia Inquirer*, refer to the levels of the predicted variables 6 and 12 months hence. The initially published average forecasts contain frequent adjustments intended to allow for large changes in the data between collection and publication. Carlson (1977) concluded that these adjustments cannot be justified, and he eliminated them by reworking the averages from the original individual forecasts. The effective spans of the forecasts were now assumed to be 8 and 14 months. Subsequent research work generally relied on the means and standard deviations of the Livingston forecasts in the form published by Carlson. Bomberger and Frazer used these data for the 8-month forecasts in 1952–77. Their S_t measure is an average of squared past errors of the individual forecasts with a geometrically weighted lag distribution.

4. On the evidence for the Livingston data, see Pesando 1975, Carlson 1977, Wachtel 1977, Pearce 1979 and Figlewski and Wachtel 1981 (more favorable results are reported in Mullineaux 1978, 1980*a*). On the evidence from other surveys of economists, consumers, and business executives, see also de Leeuw and McKelvey 1981, Gramlich 1983, and Zarnowitz 1985a.

unemployment rates as in the "stagflation" of the 1970s (M. Friedman 1977), as well as the role of monetary shocks and price misperceptions in business cycles (Lucas 1975, 1977).

Evidence from actual price index data on the whole supports the idea that a positive relationship exists between the rate of inflation and its variability over time (R. J. Gordon 1971; Okun 1971; B. Klein 1975). Additional support comes from international cross-section studies that suggest that countries with higher average rates of inflation tend to have higher standard deviations or mean absolute changes of inflation (Logue and Willett 1976; Jaffee and Kleiman 1977; Foster 1978).

Wachtel (1977) shows that the inflation expectations of economists and consumers (collected by Livingston and the Survey Research Center of the University of Michigan, respectively) have had large errors, mostly of underestimation. Nevertheless, these data contribute to equations for consumption, prices, wages, and interest rates when used along with other determinants (for some qualifications, see de Menil 1977). Cukierman and Wachtel (1979) find that for both of these surveys, the variance of inflation predictions across the respondents increases with the variance of measured inflation.

According to Mullineaux (1980b), the unemployment rate U_t falls with the unexpected part of the current inflation rate, $\pi_t^u = \pi_t - \pi_t^e$, and rises with σ_{t-i} and U_{t-j}, where π_t^e and σ_t are Carlson estimates of means and standard deviations of the Livingston survey forecasts, and the lags $i = 0, \ldots, 11$ and $j = 0, \ldots, 4$ years. However, the interpretation of these equations is difficult because of the use of long distributed lags in the presence of highly autocorrelated variables, notably U and σ. The cumulative effects on U of σ and, especially, π^u are weak in the sense that they require long lags to get significantly large with the expected signs.

In Levi and Makin 1980, the percentage change in employment dN_t depends positively on π_t^u and inversely on σ_t. The equations yield significantly positive correlations only when σ_t is included.[5] Makin (1982) relates dN_t, or its counterpart for output, to "anticipated" and "unanticipated" money growth rates, current and lagged, and to σ_{t-i}, $i = 0, 1$. Again, inflation uncertainty represented by σ is found to act as a significant depressant (the other conclusion is that anticipated money has substantial initial effects in stimulating real economic activity). These studies do not rely critically on distributed lags and are therefore more convincing.

Expectational data from the same surveys have also been used in several recent studies of the determinants of nominal yields (i_t) on bonds free of default risk. Here typically a reduced-form "Fisher equation" is estimated, where i depends on π^e, σ, and some factors affecting aggregate demand and

5. For 1948–75, however, the $\bar{R}^2$ coefficients are low, about .1–.2. For 1965–75, a period of rising and more variable inflation, they are much higher: near or above .6.

supply such as exogenous expenditures and money growth rates (or surprises).[6] Levi and Makin (1979), Bomberger and Frazer (1981), and Makin (1983) present regression estimates that show that the interest rates are negatively influenced by the current values of σ_t or distributed lags in this variable. However, Barnea, Dotan, and Lakonishok (1979) and Brenner and Landskroner (1983) report positive coefficients of σ or related proxies, while Melvin (1982) has a positive but not significant coefficient, which he suggests may be due to defects of the survey measure and the consequent errors-in-variables bias toward zero.

These apparently contradictory results may merely indicate that the sign of the effect of σ on i is not clear. The argument is that inflation uncertainty depresses both real investment and savings as borrowers and lenders are discouraged by expected volatility of relative and absolute prices. If the impact on investment dominates, the net effect of σ on the after-tax real rate and hence on i will be negative; if the impact on savings dominates, that effect will be positive (Makin 1983).

The models under review are products of the 1970s, a period of rising inflation; it is not clear that they pass the test of the disinflation in the 1980s. The sharp decline in actual inflation was accompanied by less volatility of price change. There can be little doubt that it induced lagging but substantial reductions in expected inflation and presumably also in the associated uncertainty. Yet, even when real growth was positive, the rates of productivity, investment, and saving remained on the whole low in these years (puzzlingly so to many observers), except for the strong but brief recovery in 1983–84. Interest rates declined generally but much less than inflation.[7] Recent attempts to explain these developments rely on various special factors.

17.1.4 Further Steps

Evidently, economics of uncertainty is an important and active field of study, with interest centering on inflation.[8] Just as clearly, there is as yet little well-tested knowledge about it.

The approach to be followed here is to elicit information on uncertainty from time series of probabilistic forecasts. Section 17.2 presents the data and measures we have developed.

6. Some of these studies also consider the roles of taxes, real rates, and lags, whereas others are limited to the gross effects on i_t of π^e_t and σ_t or related measures. For comprehensive surveys of the literature, see Tanzi 1984.

7. Note that the downward movement of the rates occurred entirely during the recessions of 1980 and 1981–82 as well as the slowdown after mid-1984; it was interrupted and partially reversed in the intervening recoveries.

8. Uncertainty about real growth prospects has received little attention in recent literature. The effects of changes in the "confidence" of consumers, investors, and business people are often emphasized, but these changes themselves and their determinants are extremely difficult to measure and analyze. What is needed here is probabilistic forecasts for real economic activity. Our surveys provide such materials but only since mid-1981 (see sec. 17.2).

Section 17.3 discusses the results based on these materials and compares them with the results obtained by means of the point forecast proxies for uncertainty. This is presumably the best way to answer the empirical question of just how well the indirect measures have worked. The use of matched probabilistic and point forecast sets allows us to examine directly how consensus and uncertainty are related and also whether expectations of higher inflation breed more inflation uncertainty (secs. 17.3.1–17.3.4). Next we explore ways to bring together the measures derived from our series of probabilistic forecast distributions and the measures derived from the Livingston point forecast data. This cross-section analysis is then extended to reexamine the hypotheses discussed above on how inflation uncertainty affects real economic activity and inflation rates (secs. 17.3.5–17.3.7).

Section 17.4 sums up our conclusions.

17.2 Data and Measures

17.2.1 Properties of Surveys and Samples

The survey conducted quarterly since 1968 by the American Statistical Association (ASA) and the National Bureau of Economic Research (NBER) is, to our knowledge, unique in regularly yielding numerical replies on predictive uncertainty. A questionnaire, mailed to a broadly based and diversified list of persons who are professionally engaged in the analysis of current and prospective business conditions, asks for forecasts on a number of important macroeconomic variables including the gross national product in current dollars (GNP) and in constant dollars (RGNP) and the GNP implicit price deflator (IPD). These predictions refer to the current and the next four quarters and to the current and next year.

In addition to these point forecasts, the ASA-NBER survey provides probabilistic forecasts for IPD and GNP (through mid-1981) and for IPD and RGNP (thereafter). For each of the paired variables, a list of percentage intervals (e.g., 10.0–10.9, 9.0–9.9, etc.) is included, with blank spaces to write the numbers in. The replies represent the chances in 100 that the forecaster associates with the changes falling in the selected intervals.

Although the numbers refer to *annual* changes, they come from *quarterly* surveys so that the effective horizons of the predictions vary substantially. Of principal interest are the probabilistic forecasts for the change from year $t-1$ to year t that were issued in the four consecutive surveys from the last quarter of $t-1$ through the third quarter of t. The distances between the dates of these surveys and the end of the target year are approximately 4½, 3½, 2½, and 1½ quarters. We shall refer to these categories simply as horizons (H) 4, . . . , 1. They account for the bulk of the more than 4,600 reported probabilistic forecast distributions for 1969–81 and can be regularly matched with the point forecasts made by the same persons for the same targets.

The total number of persons who responded to any of the 51 ASA-NBER surveys taken during the period 1968:4–1981:2 is 192; the number of those who participated in at least 12 surveys is 80. The latter subset of "regular" respondents is the main source of evidence in this paper, but we analyzed the total set as well to make sure that the selection does not bias our results in any particular way.

Data from the completed questionnaire forms available in the NBER files were screened so as to (1) strictly match the probabilistic and point forecasts made by the same persons for the same targets and (2) eliminate unusable replies and obvious reporting errors. The last step improved the quality of microdata in our sample but had minimal effects on the aggregate measures obtained since the proportion of the forecasts excluded was very small.

The final collection for the group of regular forecasters includes 1,673 and 1,705 individual probability distributions for GNP and IPD, respectively. The shortest forecasts (H1) account for about 19% of these data, H2 for 27%, H3 for 28%, and H4 for 26%.[9]

17.2.2 Aggregate Probabilistic and Point Forecast Series

Summary statistics such as the mean, standard deviation, skewness, and kurtosis were calculated for each of the individual probability distributions.[10] Uniform distribution within each of the selected intervals was assumed. Thus the kth-order moment about zero of the distribution is computed by numerical integration as

$$\mu_k^o = \sum_i p_i\left(\frac{u_i^{k+1}}{k+1} - \frac{l_i^{k+1}}{k+1}\right), \tag{1}$$

where p_i is the probability assigned to the ith interval ($\Sigma_i p_i = 1$), and l_i and u_i are the lower and upper limits of the ith interval, respectively. Since unit intervals are used, the mean ($k = 1$) reduces to $\Sigma_i p_i[(l_i + u_i)/2]$. The mean forecast implicit in the jth respondent's probability distribution for horizon h and year t will be denoted as ϕ_{jht}.

For each ϕ_{jht} there is a matching point forecast f_{jht}. The latter numbers are computed from corresponding estimates and predictions of *quarterly levels* of GNP and IPD. For example, in the fourth quarter of year t_{04}, a respondent would use data on the "actual" values of GNP in the preceding quarters

9. The probabilistic predictions issued in the second and third quarters of year $t-1$ (H6 and H5) and in the fourth quarter of year t (H0) are excluded. Such replies are available only for the years 1974, 1980, and 1981. Also, only 136 (about half) of them have point counterparts. The probabilistic distributions with the horizons of 6 and 5 quarters cannot be matched with point forecasts at all, and those with the zero horizon lack interest since by the fourth quarter of t most of the target year is already over. In addition, 210 faulty or unusable replies were eliminated by editing the questionnaires for degenerate distributions with single "100" entries (116), cases in which the probabilities do not add up to 1.00 (47), and mistaken applications to real rather than nominal GNP (47).

10. The results reported below are not affected by skewness and kurtosis, and no use will be made of these measures in this paper.

(. . . A_{02}, A_{03}) and make predictions through the end of the year $t+1$ (P_{04}, P_{11}, . . . , P_{14}). Accordingly, the annual percentage change forecast for any j and t and for $h = 4$ is

(2) $$f_4 = \left(\frac{P_{11} + P_{12} + P_{13} + P_{14}}{A_{01} + A_{02} + A_{03} + P_{04}}\right)100.$$

Similarly, f_3 made in the first quarter of the year $t+1$ would equal the ratio $100(\Sigma_{j=1}^{4} P_{1j} / \Sigma_{j=1}^{4} A_{0j})$, where the P's and A's are the new quarterly level predictions and estimated realizations, respectively (note that P_{04} is now replaced by A_{04}). Still more recent predictions and estimates would be available for f_2 (including A_{11} instead of P_{11}) and f_1 (including also A_{12} instead of P_{12}).

The individual ϕ and f predictions are used next to construct annual time series of group averages. Thus the means of the individual probability distributions are averaged across all members of the sample for the given survey as in

(3) $$\sum_j \phi_{jht} = \Phi_{ht}.$$

The matching point forecasts are similarly averaged over the same individuals according to

(4) $$\sum_j f_{jht} = F_{ht}.$$

These steps produce 2×4 aggregate probabilistic forecast series and again 2×4 aggregate point forecast series (for GNP and IPD, and $h = 1, \ldots, 4$, in each case).

17.2.3 Regular and Occasional Forecasters

Whether or not the sporadic respondents are included makes hardly any difference in terms of the aggregate results. For both GNP and IPD, the corresponding average measures in the total set and the regular set are extremely close. This applies to mean forecasts, mean errors, and the overall dispersion statistics for point forecasts and probabilistic forecasts alike, as demonstrated in table 17.1, lines 5–6, 11–12, and 17–18. Correlations between the two sets are so uniformly near unity, even after squaring and adjusting for the degrees of freedom, that there is no need to list them. Suffice it to note that the $\bar{r}^2$ between the matched "all" and "12+" mean forecasts exceed .99 for either variable at each horizon and that they are not much lower for the other statistics. For example, the average $\bar{r}^2$ is .96 for the series of standard deviations of the corresponding probabilistic forecasts.

The evidence from the ASA-NBER surveys presented below is based on the forecasts by the "regular" respondents only, that is, those who participated in 12 or more surveys. There are several good reasons for working with this group. Earlier studies of the samples of individual forecasts from these sur-

Table 17.1 **Summary Statistics for Point Forecasts and Mean Probability Forecasts of Annual Percentage Changes in GNP and IPD, 1969–81**

		Gross National Product		Implicit Price Deflator	
Line	Horizon (quarters)[a] (1)	Point Forecasts (2)	Mean Probability Forecasts (3)	Point Forecasts (4)	Mean Probability Forecasts (5)
			Mean Forecasts		
1	1	8.8 (2.8)	8.4 (2.6)	6.6 (1.9)	6.6 (2.1)
2	2	8.9 (2.6)	8.8 (2.4)	6.2 (2.2)	6.4 (2.2)
3	3	9.0 (2.2)	9.0 (2.1)	6.2 (2.4)	6.4 (2.4)
4	4	8.7 (2.1)	8.6 (2.0)	5.2 (1.8)	5.5 (1.8)
5	1–4	8.9 (2.4)	8.7 (2.3)	6.1 (2.1)	6.2 (2.1)
6	1–4 (all)	8.8 (2.4)	8.7 (2.3)	6.1 (2.1)	6.2 (2.0)
			Mean Errors[b]		
7	1	−.44 (1.32)	−.79 (1.14)	−.19 (.47)	−.22 (.54)
8	2	−.62 (1.13)	−.73 (1.01)	−.50 (.73)	−.38 (.80)
9	3	−.64 (.97)	−.70 (1.01)	−.72 (1.13)	−.52 (1.16)
10	4	−.88 (.85)	−1.01 (.88)	−1.20 (1.42)	−.92 (1.47)
11	1–4	−.65 (.18)	−.81 (.14)	−.65 (.42)	−.51 (.30)
12	1–4(all)	−.67 (.21)	−.84 (.19)	−.66 (.43)	−.50 (.31)
			Standard Deviation[c]		
13	1	.39 (.11)	.81 (.06)	.34 (.21)	.76 (.06)
14	2	.63 (.23)	.91 (.07)	.46 (.20)	.83 (.08)
15	3	.90 (.31)	.98 (.10)	.68 (.34)	.90 (.11)
16	4	1.14 (.22)	.98 (.08)	.70 (.19)	.86 (.07)
17	1–4	.76 (.32)	.92 (.08)	.54 (.23)	.84 (.08)
18	1–4 (all)	.83 (.43)	.94 (.08)	.59 (.20)	.84 (.08)

Note: All entries refer to the samples of regular forecasters except those in lines 6, 12, and 18, which refer to the samples of all forecasters. Entries are means; entries within parentheses are the corresponding standard deviations. All measures are in percentage points, referring to percentage changes at annual rates.

[a]Horizons 1, 2, 3, and 4 refer to forecasts of change from year $t - 1$ to year t made in the third, second, and first quarters of year t and the fourth quarter of year $t - 1$, respectively; 1–4 refers to forecasts for all four horizons combined. See n.14 and the text for more detail.

[b]Entries in lines 7–10 are averages of the series shown in fig. 17.1.

[c]Entries in lines 13–16 are averages of the series shown in fig. 17.2.

veys (see chapters 15 and 16) had to impose some minimum-response restrictions since the sporadic respondents could not be individually evaluated because of a paucity of data. The "12 or more" rule was used there to good advantage, and the approach is followed here in the interest of consistency and comparability. The elimination of occasional forecasts also has the advantage of reducing the variation of the coverage over time.[11]

11. Many individuals responded only once or a few times, mainly to the early surveys. Each of the 80 "regulars" had an adequate exposure: the range is 12–34 surveys, with a mean of 23 and a standard deviation of 8. The numbers of participants per survey in this sample average 41, with a standard deviation of 10 and a range of 21–60.

17.3 Results

17.3.1 Mean Forecasts and Errors

Figure 17.2 shows a remarkably close agreement between paired series of group mean errors of probabilistic and point forecasts and, by implication, also between the corresponding mean forecast series.[12] Indeed, Φ_{ht} and F_{ht} are highly correlated in each of the eight cases, with $\bar{r}^2$ ranging from .881 to .992 for GNP and from .981 to .995 for IPD. The matched series have very similar average levels, as can be seen in table 17.1, lines 1–12.

This is a strong finding of considerable significance. Evidently, the respondents on the whole equated their preferred (point) forecasts to the expected values (weighted means) of their predictive probability distributions. To be sure, not all did so at all times, but a large majority did most of the time. Thus large $\phi - f$ discrepancies being well defined as exceeding 1 percentage point, only about one in four of the regular respondents had 20% or more of such deviations on the record, and only one in twenty had 40% or more.

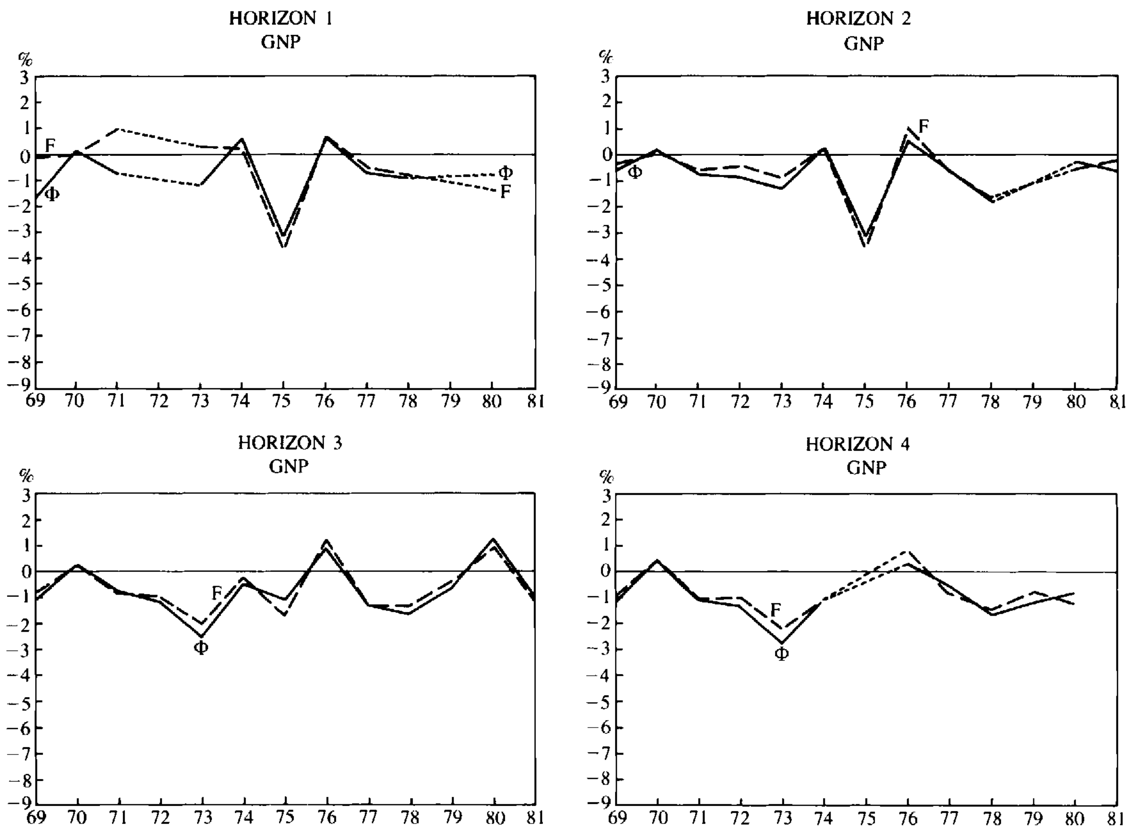
For unbiased forecasts, these results seem mildly suggestive of symmetrical loss functions, but they are not inconsistent with bias or asymmetrical loss functions for many of the individuals involved. Indeed, figure 17.2 indicates that the surveyed forecasts are not free of bias. Of the 46 mean errors of probabilistic predictions for GNP, H1–H4, 35 (76%) are negative; the parallel count for IPD is 31/46 (67%). The proportions of underestimates among the mean errors of point predictions are 76% for GNP and 74% for IPD. Not only are the underestimates more numerous than the overestimates, but they also are visibly larger overall. On the average, the errors of both the probabilistic and the point forecasts are negative for either variable at each horizon (table 17.1, lines 7–12). The absolute values of these mean errors tend to increase with the horizon, especially for IPD, where the corresponding variability measures do so as well (see entries in parentheses).[13]

17.3.2 Series of Dispersion Measures

Figure 17.3 compares the series of the means of the standard deviations calculated from the individual probability forecast distributions ($\bar{s}_\phi$) with the series of standard deviations for the corresponding sets of point forecasts (s_f). For the GNP growth rates, $\bar{s}_\phi > s_f$ in each year at H1 and in all but two years at H2, but the differences between $\bar{s}_\phi$ and s_f are much smaller and less systematic at H3 and H4. For the IPD inflation rates, $\bar{s}_\phi$ exceeds s_j as a general rule

12. Note that $(\Phi_{ht} - A_t) - (F_{ht} - A_t) = \Phi_{ht} - F_{ht}$. Also, for any group of respondents indexes $j = 1, \ldots, n$, $\Sigma_j^n(\phi_j - A) = \Phi - A$ and $\Sigma_j^n(f_t - A) = F - A$ (this applies to any h and t, so these subscripts are omitted for simplicity).

13. Unlike inflation, which was heavily underestimated in this period, real GNP growth rates were on the average overestimated, so that the *quarterly* point forecasts of changes in nominal GNP show little bias (see chapters 14 and 16). However, the mean errors of GNP forecasts for the successive quarters, while small, are generally negative, and they cumulate. This produces much larger underestimation errors in the *annual* forecasts.


HORIZON 1
GNP
HORIZON 2
GNP
HORIZON 3
GNP
HORIZON 4
GNP
%
3
2
1
0
−1
−2
−3
−4
−5
−6
−7
−8
−9
69
70
71
72
73
74
75
76
77
78
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80
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F
Φ

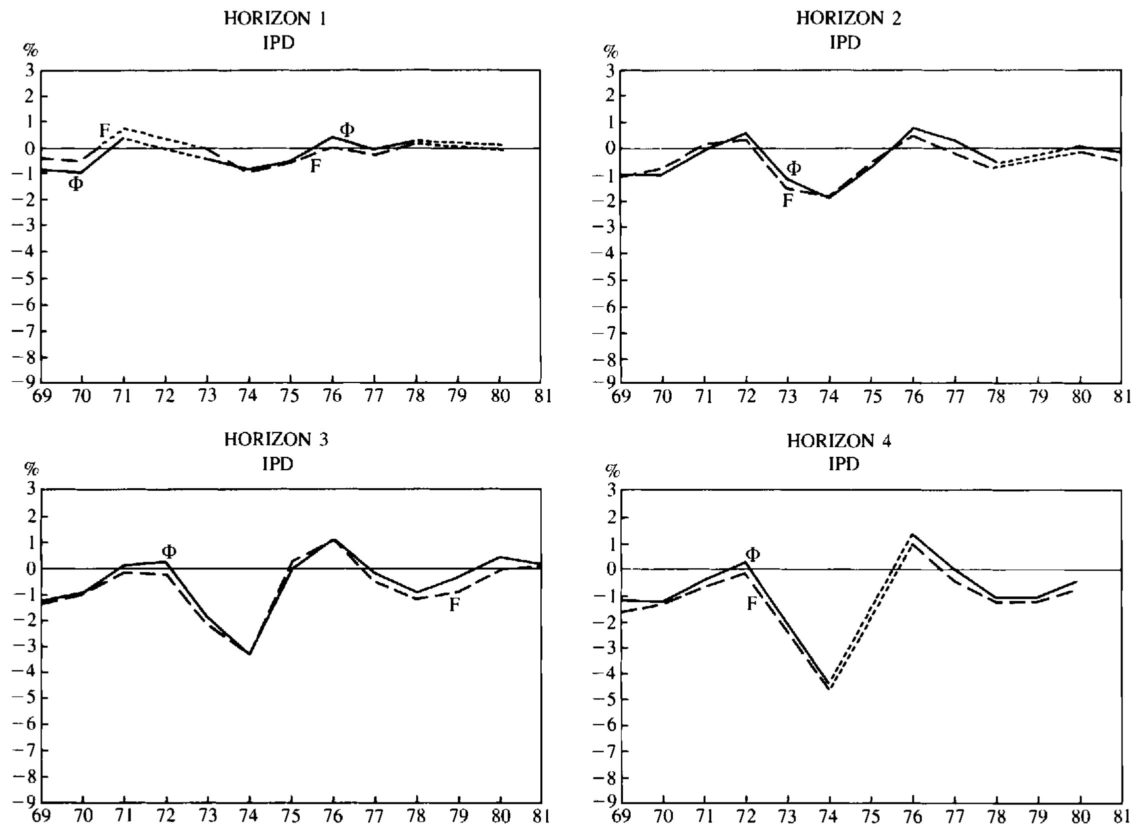


Fig. 17.2 Mean errors in point and probabilistic forecasts of rates of change in GNP and IPD, four horizons, annual, 1969–81
Note: Long-dashed lines refer to mean errors of group forecasts (F_{ht}); solid lines refer to mean errors of group probabilistic forecasts (Φ_{ht}); short-dashed lines indicate missing observations. The actual values used to compute the forecast errors are the last estimates available prior to the benchmark revisions of January 1976 and December 1980.

(with exceptions of one year each at H1 and H2 and two years each at H3 and H4). The $\bar{s}_\Phi$ series fluctuate much less over time than their s_f counterparts.

Table 17.1 quantifies some of the inferences from these graphs (lines 13–16). The $\bar{s}_\Phi$ series (cols. 3 and 5) are relatively stable, as shown by the figures in parentheses, and they increase only mildly between H1 and H3. In contrast, the s_f series (cols. 2 and 4) are volatile and increase strongly and monotonically with the horizon from much lower levels at H1. The differences $\bar{s}_\Phi - s_f$ are positive and relatively large in six of the eight categories (for GNP H3 the difference is small; for GNP H4 it is negative).

Disturbances to aggregate demand and the price level come largely without warning and are unanticipated; most are then followed by gradual adjustments. There is a great deal of inertia and resilience in the economy, whose normal condition is growth, and the agents-observers know it. It seems, prima facie, unlikely that uncertainties about demand growth and inflation would vary as widely and erratically from year to year as the s_f series do, even in turbulent times, and that they would differ so much across the horizons. What can reasonably be expected is that increases in the volatility of change, whether in spending or prices, will in time generate irregular upward drifts in the corresponding uncertainties. The $\bar{s}_\Phi$ series show in each case much less variability than the s_f series but also generally higher and more gently rising levels. We find the behavior of $\bar{s}_\Phi$ easier to rationalize with respect to the presumptive measures of uncertainty than the behavior of s_f.

Our results thus suggest that consensus statistics probably often understate the levels of uncertainty. They may also overstate the variations in uncertainty. Measures based on the probabilistic forecast distributions should be more dependable on both counts.

17.3.3 Is Predictive Dissent a Symptom of Uncertainty?

Table 17.2 shows that a unit increase in s_f may add only a fraction to $\bar{s}_\Phi$: the regression coefficients are of the order of .1–.2, where they appear significant at all (col. 4). The intercepts are all very similar, somewhat above .7 for inflation, higher for the rates of change in GNP (col. 3). The Durbin-Watson statistics are not very low, generally close to 1.5 (col. 5). Of the 12 correlations listed, five are significant at the 1% level or better, which includes the results from pooling the data across the horizons, and two others are significant at the 10% level; none of the rest presumably differs statistically from 0 (in four cases $\bar{r}^2 = 0$).

The evidence, then, is mixed, much of it suggesting that s_f and $\bar{s}_\Phi$ are at most weakly related. But this needs to be qualified by two observations. First, all but two of the correlations listed (both for the shortest forecasts, H1) are positive. Second, when larger samples are obtained by pooling and when there are no missing observations (H3), the results rather clearly indicate a positive association between s_f and $\bar{s}_\Phi$. Thus there is some direct empirical support here for what is often taken for granted, namely, that greater interpersonal differentiation of expectations is a symptom of greater uncertainty.

The reasons why this support is not stronger may lie in certain offsetting effects. Thus one can argue that it is precisely when uncertainty is high that people will have strong incentives to reduce the risk of making eccentric errors and will invest more resources in interactive prediction (see sec. 17.1.1). To the extent that this is true, it would tend to make the individual expectations (point forecasts) more closely bunched at such times; that is, it would produce elements of inverse correlation between s_f and $\bar{s}_\Phi$.

A warning is in order at this point. Our findings are based on small samples of observations. Pooling the data can help but is no substitute for longer series of matching point and probabilistic forecasts. Collection and processing of more information of this type should in time produce more conclusive results.

17.3.4 Inflation Expectations and Uncertainty

Our data permit direct tests of the hypothesis that changes in anticipated inflation tend to cause parallel changes in uncertainty about inflation. This idea plays an important role in theories that view rising (and high and volatile) inflation as a major source of adverse real effects (see sec. 17.1.3).

Table 17.3 shows that the regressions of inflation uncertainty measured by $\bar{s}_\Phi$ on inflation expectations measured by Φ give results that are generally consistent with the hypothesis. The effects of Φ on $\bar{s}_\Phi$ are all positive, and they are strong for all except the shortest (H1) forecasts, as shown by the t-ratios on b, the Durbin-Watson statistics, and the correlations (lines 1–4, cols. 3–6). Pooling yields good results, too, especially when dummy variables are used to capture the horizon effects (lines 5–6).

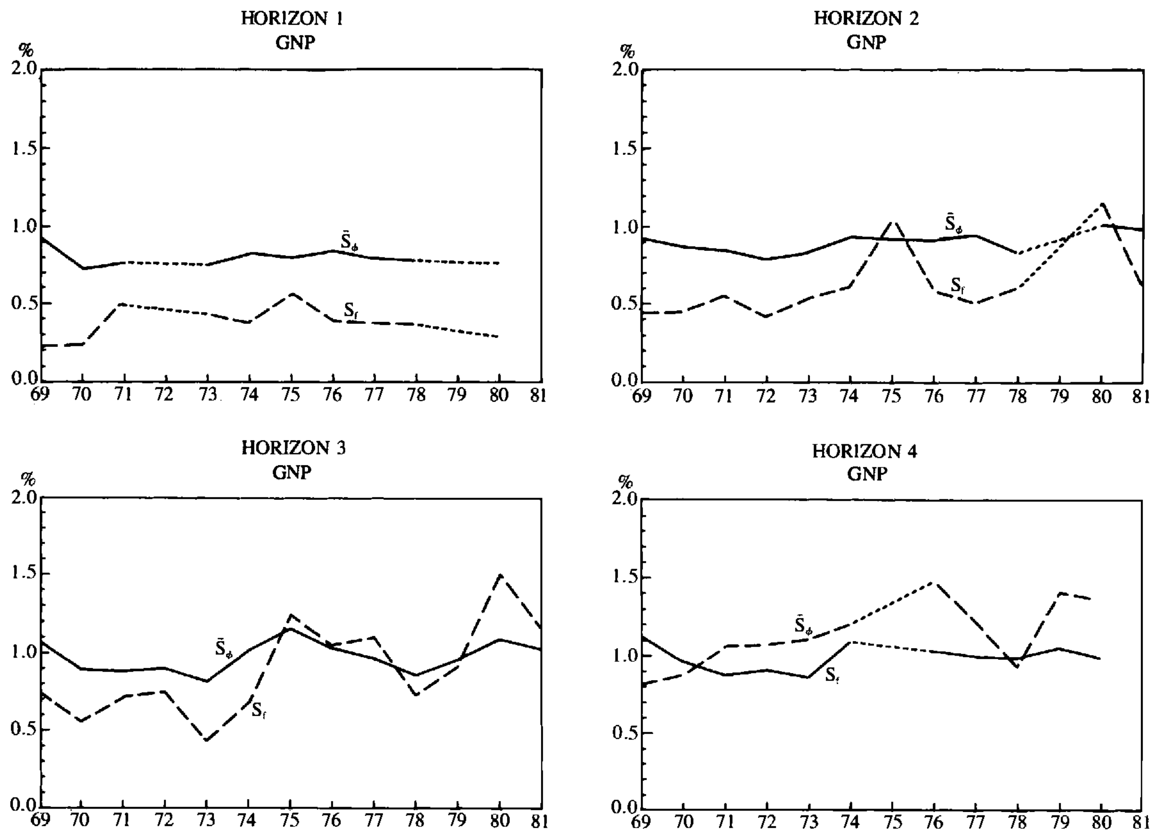
In contrast to this direct supportive evidence from the probabilistic forecast distributions, the consensus measures from the point forecasts contribute little here. The effects of F on s_f are weak generally and apparently trifling for H1 and H2, although the correlations between the two variables are all positive (lines 7–10). Pooling does not help, except for the significant horizon effects (lines 11–12).

That higher Φ is associated with higher $\bar{s}_\Phi$ for inflation does not mean that a similar relationship should be expected to exist for GNP, which reflects changes in total output as well as in the price level. There is no presumptive reason why increased rates of real growth ought to induce greater uncertainty about growth prospects, for example. Indeed, the correlations between $\bar{s}_\Phi$ and Φ for GNP are extremely low, with $\bar{R}^2 = 0$ for each horizon. The pooled regressions show no significant effects of Φ on $\bar{s}_\Phi$ either.[14] Much the same applies to the F and s_f series derived from the GNP point forecasts, where one

14. When dummy variables for the horizons are used, they alone contribute to the regression, as shown by the following estimates:

$$\underset{}{\bar{s}_\Phi} = \underset{(14.9)}{.798} + \underset{(.25)}{.0014\Phi} + \underset{(2.8)}{.099d_2} + \underset{(5.0)}{.171d_3} + \underset{(4.9)}{.174d_4},$$

$$R = .664,\ \bar{R}^2 = .386.$$



HORIZON 1
GNP
%
2.0
1.5
1.0
0.5
0.0
69
70
71
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$\bar{S}_\phi$
S_f
HORIZON 2
GNP
HORIZON 3
GNP
HORIZON 4
GNP

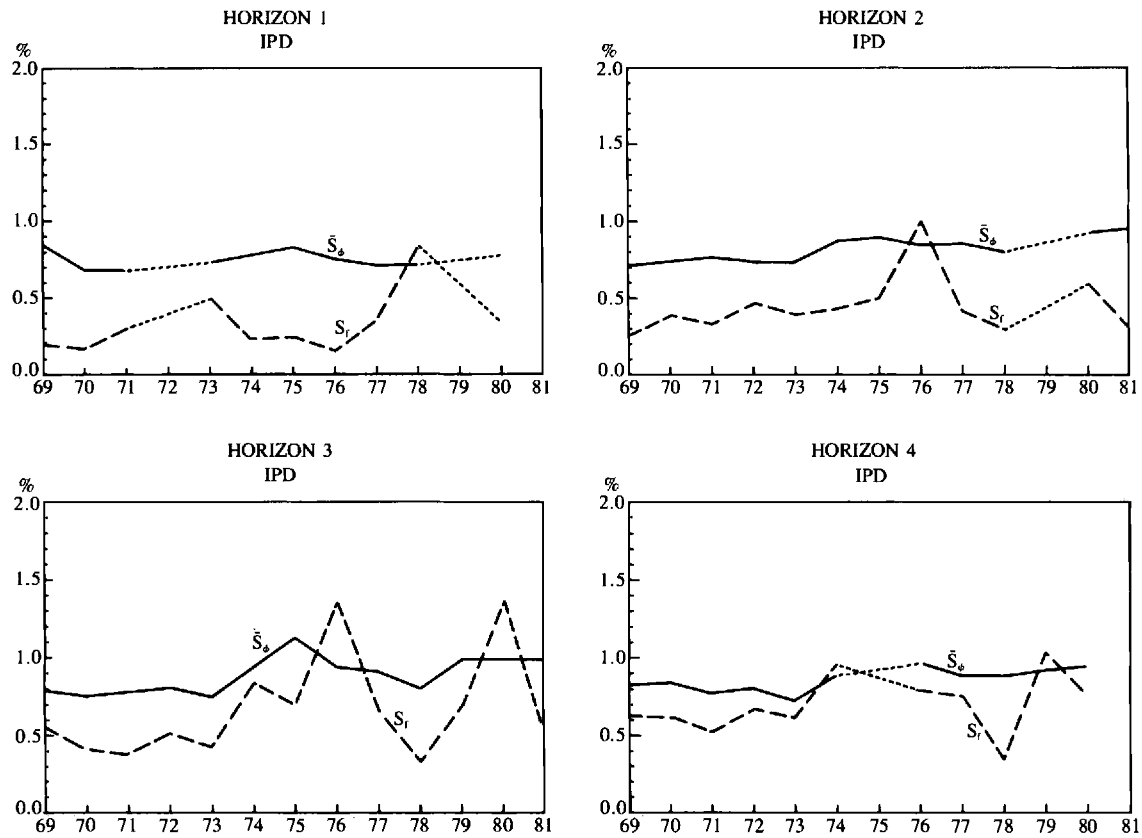

Fig. 17.3 Standard deviations and probabilistic forecasts of rates of change in GNP and IPD, four horizons, annual, 1969–81
Note: Long-dashed lines refer to standard deviations of point forecasts (s_f); solid lines refer to standard deviations of probabilistic forecasts (s_Φ); short-dashed lines indicate missing observations.

Table 17.2 **Relating Time Series of Standard Deviations of Point and Probabilistic Forecasts, Annual Percentage Changes in GNP and IPD, 1969–81**

			Regression Estimates[a]			Correlations[b]	
Line	Horizon (quarters) (1)	No. of Observations (2)	*a* (3)	*b* (4)	Durbin-Watson (5)	*r* (6)	$\bar{r}^2$ (7)
			Gross National Product				
1	1	10	.885	−.118	2.08	−.237	0
			(12.5)	(−.7)			
2	2	12	.810	.157	1.64	.545**	.226
			(15.8)	(2.0)**			
3	3	13	.753	.255	1.03	.758*	.536
			(12.1)	(3.9)*			
4	4	11	.934	.044	1.48	.114	0
			(6.3)	(.3)			
5	H1–H4, pooled	46	.764	.209	1.48[†]	.710*	.493
			(28.8)	(6.7)*			
6	With dummies[c]	46	.744	.168	1.59[†]	.756*	.530
			(25.6)	(3.6)*			
			Implicit Price Deflator				
7	1	10	.785	−.078	1.63	−.280	0
			(21.2)	(−.8)			
8	2	12	.774	.120	.79	.295	0
			(12.6)	(1.0)			
9	3	13	.772	.181	1.97	.534**	.221
			(11.9)	(2.1)**			
10	4	11	.736	.179	1.27	.467	.131
			(9.0)	(1.6)			
11	H1–H4, pooled	46	.740	.182	1.59[†]	.525*	.259
			(27.0)	(4.1)*			
12	With dummies[d]	46	.714	.131	1.56[†]	.606*	.306
			(23.1)	(2.6)*			

[a]The regression equations are $\bar{s}_{\phi} = a + bs_f$ (with the time subscripts omitted; there are no lags); *t*-ratios are in parentheses.

[b]Multiple correlation coefficients R and $\bar{R}^2$ appear in lines 6 and 12.

[c]The coefficients of the dummy variables H2, H3, and H4 (and their *t*-ratios) are .059 (1.8)**, .086 (2.2)***, and .049 (1.0), respectively.

*Significant at the 1% level for two-tail tests.

**Significant at the 10% level for two-tail tests.

***Significant at the 5% level for two-tail tests.

[†]Exceeds the upper bound of the 1% point.

of the correlations is negative and only one (for H4) is positive and significant at the 10% level.

17.3.5 Cross-Survey Analysis

The literature discussed in section 17.1.3 makes extensive use of measures based on the point forecasts of inflation from the Livingston surveys. How are

Table 17.3 Relating Standard Deviations to Means of Probabilistic and Point Forecasts of Inflation, 1969–81

		Regression Estimates[b]			Correlations[c]	
Line	Horizon (quarters)[a] (1)	a (2)	b (3)	Durbin-Watson (4)	r (5)	$\bar{r}^2$ (6)
		Probabilistic Forecasts				
1	1	.686	.011	1.56	.404	.058
		(11.3)	(1.2)			
2	2	.600	.036	1.78	.954*	.902
		(25.4)	(10.1)*			
3	3	.620	.043	1.66	.887*	.767
		(13.6)	(6.4)*			
4	4	.660	.037	1.91	.869*	.728
		(16.5)	(5.3)*			
5	H1–H4, pooled	.653	.030	.70	.647*	.406
		(18.6)	(5.6)*			
6	With dummies[d]	.540	.033	1.72[†]	.868*	.730
		(18.6)	(9.0)			
		Point Forecasts				
7	1	.218	.018	1.87	.167	0
		(.8)	(.5)			
8	2	.383	.011	2.00	.130	0
		(2.0)	(.4)			
9	3	.299	.061	2.50 ·	.432	.114
		(1.2)	(1.6)			
10	4	.446	.049	2.72	.455	.119
		(2.5)	(1.5)			
11	H1–H4, pooled	.415	.022	1.46[†]	.167	.006
		(3.2)	(1.1)			
12	With dummies[e]	.089	.376	2.30[†]	.599*	.296
		(.6)	(2.2)			

[a]For the corresponding numbers of observations, see table 17.2.

[b]The regression equations are $\bar{s}_\Phi = a + b\Phi$ for the probabilistic forecasts (lines 1–6) and $s_f = a + bF$ for the point forecasts (lines 7–12) with the time subscripts omitted (there are no lags); t-ratios are in parentheses.

[c]Multiple correlation coefficients R and $\bar{R}^2$ appear in lines 6 and 12.

[d]The coefficients of the dummy variables H2, H3, and H4 (and their t-ratios) are −.077 (3.5)*, .143 (6.7)*, and .139 (6.2)*, respectively.

[e]The coefficients of the dummy variables H2, H3, and H4 (and their t-ratios) are .132 (1.3), .353 (3.6)*, and .417 (3.9)*, respectively.

*Significant at the 1% level for two-tail tests.

[†]Exceeds the upper bound of the 1% point.

these data related to our series of probabilistic forecast measures? This question clearly needs to be addressed, but the differences between the Livingston and the ASA-NBER survey formats impede obtaining the answer.

One approach is to combine the Livingston forecasts made late in the year $t-1$ for the first half of year t with those made in the middle of year t for the second half. The resulting annual averages, called LIV6, are paired with the means of the ASA-NBER forecasts with horizons H4 and H2 for year t, labeled ANB6. The component predictions of LIV6 and ANB6 have similar dates,[15] but the targets of the former are semiannual and those of the latter are annual. This complication is avoided by an alternative procedure, which is to match the projections for t from the late $t-1$ surveys of Livingston and ASA-NBER H4 (we refer to these series as LIV12 and ANB12).

For all these differences, plus the fact that the Livingston surveys aim at the rate of change in consumer prices (CPI) while the ASA-NBER surveys aim at inflation in terms of the IPD, the mean forecasts for LIV6 and ANB6 and for LIV12 and ANB12 are highly correlated, as demonstrated in table 17.4, lines 1–2. Of course, these associations are not quite as close as those between the F and Φ series within the ASA-NBER set.

More remarkable yet, the correlations between the s_f series for LIV and the $\bar{s}_\Phi$ series for ANB are rather high and significant at the level of 1% or less (lines 3 and 4). There is more evidence here that low (high) consensus indicates high (low) uncertainty than in the relationships between the s_f and $\bar{s}_\Phi$ series within the ASA-NBER set as examined in table 17.2 and section 17.2.3.

It is true that the significance of these results is difficult to assess, given the smallness of the available data samples. Pooling cannot be used here to alleviate the problem. The Durbin-Watson statistics are not very low, but the residuals from some of the regressions appear to be positively autocorrelated.

In the ANB series used in table 17.4, H3 figures are interpolated in the instances in which H2 or H4 figures are not available. However, to guard against a possible bias from this procedure, alternative regressions were calculated discarding all observations for which the H2 or H4 forecasts are missing.[16] The main results of this procedure for the equations $s_f = a + b\bar{s}_\Phi$ are the following: for LIV6–ANB6, $b = 5.600$ (3.6); D-W = 2.31, $r = .784$; for LIV12–ANB12, $b = 3.988$ (3.8); D-W = 2.34, $r = .788$ (t-ratios and r significant at the 1% level in a two-tail test). Compared with their counterparts in table 17.4, the values of the t-ratios and r are lower here and the Durbin-Watson statistics much higher. The finding that the LIV s_f series are positively related to the ANB $\bar{s}_\Phi$ series remains intact, so the interpolations seem to have little to do with it.[17]

15. The Livingston midyear and end-of-year surveys are taken about a month after the corresponding ASA-NBER surveys (see table 17.4, n. *a*).

16. This "classical least squares" method of dealing with the problem of missing observations is used throughout elsewhere in this study.

17. There is also no evidence that the interpolations cause any serious distortions in the other equations estimated in table 17.4. Without interpolations, the t-ratios of b and r values are somewhat higher in lines 1 and 2, somewhat lower in lines 5–8, but all are still significant at the level of 1% or less. The Durbin-Watson statistics are generally higher, exceeding 2.3 in all but three cases, which suggests that the interpolations might have induced some autocorrelation in the residuals from the regressions of table 17.4.

Table 17.4 Relating the Uncertainty and Consensus Measures for the ASA-NBER and Livingston Inflation Forecasts, 1969–81

		Regression Estimates[b]			Correlations	
Line	Survey Data[a] (1)	a (2)	b (3)	Durbin-Watson (4)	r (5)	$\bar{r}^2$ (6)
		Mean Forecasts (F, φ)				
1	LIV6, ANB6	−.811	1.040	1.48	.937*	.868
		(−1.0)	(8.9)*			
2	LIV12, ANB12	−.553	1.024	1.56	.956*	.906
		(−.9)	(10.8)*			
		Standard Deviations (s_f, $\bar{s}_\phi$)				
3	LIV6, ANB6	−3.058	5.470	1.29	.849*	.696
		(−3.4)	(5.3)*			
4	LIV12, ANB12	−1.854	3.480	1.50	.811*	.625
		(−2.7)	(4.6)*			
		Standard Deviations on Mean Forecasts				
5	LIV6 (s_f, F)	.426	.217	1.73	.898*	.789
		(2.1)	(6.8)*			
6	LIV12 (s_f, F)	.280	.169	1.78	.906*	.804
		(1.9)	(7.1)*			
7	ANB6 ($\bar{s}_\phi$, ϕ)	.615	.040	1.63	.954*	.902
		(24.5)	(10.6)*			
8	ANB12 ($\bar{s}_\phi$, ϕ)	.637	.041	1.17	.891*	.774
		(15.3)	(6.5)*			

[a]LIV6 are annual F and s_f series for inflation (CPI) based on forecasts from surveys taken in December of year $t - 1$ for the first half of year t and in June of t for the second half of t. LIV12 are corresponding series based on December $(t - 1)$ forecasts for year t. ANB6 are annual ϕ and $\bar{s}_\phi$ series for inflation (IPD) based on forecasts taken in November of $t - 1$ and May of t for the year t. ANB12 are corresponding series based on November $(t - 1)$ forecasts for year t.

[b]The regression equations are of the form $F = a + b\phi$ for lines 1–2, $S_f = a + b\bar{s}_\phi$ for lines 3–4, $s_f = a + bF$ for lines 5–6, and $\bar{s}_\phi = a + b\Phi$ for lines 7–8. The F and s_f series refer to LIV6 and LIV12; the Φ and $\bar{s}_\phi$ series to ANB6 and ANB12. t-ratios are in parentheses. The number of observations is 13 in each regression (for one missing observation in the H2 series and two in the H4 series, the corresponding values of H3 are interpolated).

*Significant at the 1% level for two-tail tests.

What probably does help explain these results is that they are based on 6-month and, to a larger extent, 12-month forecasts, omitting the shortest horizon for which the association between s_f and $\bar{s}_\phi$ may be much weaker, as table 17.2 would suggest. In any event, table 17.4 provides direct support for the uses of the Livingston σ series as a proxy measure of uncertainty. This seems to be the first evidence of this kind, and as such it is both noteworthy and favorable.

The last section of table 17.4 confirms that $\bar{s}_\phi$ rises with Φ (cf. lines 7–8 and table 17.3, lines 1–6), but it also shows that s_f rises with F for both the LIV6 and the LIV12 series (lines 5–6). The latter effects seem rather strong, which contrasts sharply with the evidence of weak or no relationship between s_f and F in the ASA-NBER data (see table 17.3, lines 7–12).

17.3.6 Effects on Real Growth

Table 17.5 shows that the rate of change in real GNP (DY_t) in the years 1969–81 was positively associated with the concurrent and lagged growth rates in the M1 money supply (DM_t and DM_{t-1}) and negatively associated with the concurrent level of inflation uncertainty σ_t measured by ANB12$\bar{s}_\phi$ (though ANB6 $\bar{s}_\phi$ would do about as well). The influence of the latter factor appears to be strong but not very lasting since the negative coefficient of σ_t is to a large extent offset by a positive coefficient of σ_{t-1}. However, with only these annual series at our disposal, distributed-lag relations cannot be well assessed. Similar results are obtained when the proxy measures for uncer-

Table 17.5 **Inflation Uncertainty in Equations for Real Growth, 1969–81**

Variable or Statistic[a]	Regression Equations[b] (5.1)	(5.2)	(5.3)	(5.4)	(5.5)	(5.6)
Constant	7.563	−2.034	1.251	−2.312	−.252	.272
	(1.40)	(−.36)	(.47)	(−.73)	(−.05)	(.08)
DM_t	10.939	9.715	10.487	6.470	10.054	8.496
	(2.59)	(2.03)	(2.64)	(1.21)	(2.47)	(1.54)
DM_{t-1}	. . .	4.051	. . .	7.807	. . .	. . .
		(1.07)		(2.02)		
ANB12 $\bar{s}_{\phi t}$	−11.578	−14.637	. . .	. . .	−11.092	
	(2.16)	(−2.75)			(−1.96)	
ANB12 $\bar{s}_{\phi t-1}$	. . .	12.176	. . .	. . .	11.681	. . .
		(2.27)			(2.36)	
LIV12 s_{ft}	. . .	. . .	−3.029	−4.474	. . .	−4.735
			(−2.58)	(−2.90)		(−2.67)
LIV12 s_{ft-1}	. . .	. . .	. . .	2.910	. . .	2.926
				(1.73)		(1.55)
TBR_{t-1}	. . .	. . .	. . .	. . .	−.389	. . .
					(−1.58)	
DGE_t	. . .	. . .	. . .	. . .	. . .	.198
						(1.52)
Standard error of estimate	1.930	1.531	1.811	1.528	1.416	1.667
R	.742	.896	.777	.896	.912	.875
$\bar{R}^2$	.461	.689	.525	.690	.734	.631
Durbin-Watson	2.07	1.42	2.27	2.23	1.49	2.19

Source: ANB: ASA-NBER surveys; LIV: Livingston surveys; *DM*, TBR, and *DGE*: Bureau of Economic Analysis *Handbook of Cyclical Indicators*, 1984.

Note: t-statistics are in parentheses.

[a] *DM* is the annual rate of change in the money supply, M1 (%); TBR is the 3-month Treasury bill rate; *DGE* is the annual rate of change in the total of real federal government expenditures and real exports (%); for the ANB and LIV variables, see the text and table 17.4.

[b] The dependent variable is the annual rate of change in real GNP (%) (*DY*).

tainty LIV12 s_f are used instead of ANB $\bar{s}_\phi$ (cf. eqs. [5.1]–[5.2] with eqs. [5.3]–[5.4]).

Reciprocal relations being ubiquitous in economics, the direction of causation is often difficult to establish: surely a prime example of this is that *DY* can affect *DM* as well as the other way around. But it makes good sense to argue that uncertainty about future inflation can influence real activity adversely in times of rapid and irregular rises in the price level (such as the 1970s), whereas the reverse causation is implausible here. (Why should low *DY* induce high σ?)

The *t*-ratios leave little doubt about the significance of the separate effects of the *DM* and σ variables, with a couple of possible exceptions that probably reflect collinearity problems.[18] Jointly, these variables account for about .5–.7 of the variance of *DY*, depending on whether their lagged terms are included (see the $\bar{R}^2$ coefficients). Real defense and other federal government purchases of goods and services are usually treated as an exogenous determinant of total output of the economy, and the same applies to real exports. However, adding the rate of change in real federal expenditures and exports (*DGE*) to regressions with current and lagged values of *DM* and $\bar{s}_\phi$ turned out to contribute very little or nothing.[19] The variable DGE_t was somewhat more effective (but at some expense of DM_t) when used along with the s_f series, as illustrated by equation (5.6). Also, there are some indications of a negative influence on *DY* of lagged interest rates (represented by the Treasury bill rate [TBR]), but they too are somewhat sporadic and weak (eq. [5.5]).[20]

In sum, the idea of inflation uncertainty as a short-term depressant of real activity receives substantial support from table 17.5. The Livingston s_f data provide on the whole a good proxy measure of σ in this context. These results are consistent with recent studies.[21] They seem sufficiently robust to merit cautious acceptance at this time, pending the accumulation of more evidence.

17.3.7 Effects on Interest Rates

Interest rates (*i*) represented by TBR_t depend positively on expected inflation Φ_t and inversely on inflation uncertainty $\bar{s}_{\phi t}$ and money growth DM_t, as seen in table 17.6, equation (6.1). The lagged terms Φ_{t-1} and $\bar{s}_{\phi t-1}$ enter with

18. The addition of ANB12$s_{\phi t-1}$ results in a low *t* for DM_{t-1} and reduces the Durbin-Watson statistics (which otherwise exceed 2). The addition of LIV12s_{ft-1} results in a low *t* for DM_t. The correlations between $s_{\phi t}$ and $s_{\phi t-1}$ is .463, that between s_{ft} and s_{ft-1} is .618, and for DM_t and DM_{t-1} the corresponding statistic is .410.

19. That is, neither *DY* nor the coefficients of the other variables were significantly affected. We have also tried, with similarly negative results, a series of shares of federal government purchases and exports in GNP.

20. No further search for missing variables was considered necessary or indeed desirable, given the pitfalls of data mining and our limited objectives.

21. See Levi and Makin 1980 and Makin 1982. It should be noted that this refers only to the role of ϕ_t. Our calculations were not designed to deal with the issue of anticipated versus unanticipated money growth (m^e vs. m^u); their outcome is consistent either with m^e having real effects or with m^u accounting for the largest part of total monetary change.

Table 17.6 **Inflation Expectations and Uncertainty in Equations for Interest Rates, 1969–81**

Variable or Statistic[a]	Regression Equations[b] (6.1)	(6.2)	(6.3)	(6.4)	(6.5)	(6.6)
Constant	30.930	39.915	6.943	9.067	23.068	.293
	(5.07)	(4.44)	(2.14)	(3.41)	(3.25)	(.12)
DM_t	−6.871	−6.436	−8.571	−8.949	−5.106	−4.138
	(−2.26)	(−1.51)	(−1.73)	(−2.25)	(−1.75)	(−1.31)
ANB12 ϕ_t	2.558	1.883	. . .	. . .	2.717	. . .
	(6.47)	(2.66)			(7.38)	
ANB12 ϕ_{t-1}	. . .	1.382	. . .	. . .	. . .	. . .
		(1.40)				
ANB12 $\bar{s}_{\phi t}$	−40.110	−33.273	. . .	. . .	−32.956	. . .
	(−4.71)	(−3.43)			(−3.79)	
ANB12 $\bar{s}_{\phi t-1}$	. . .	−21.760	. . .	. . .	. . .	. . .
		(−1.51)				
LIV12 F_t	. . .	. . .	1.739	1.831	. . .	1.684
			(2.71)	(3.53)		(4.36)
LIV12 F_{t-1}	. . .	. . .	. . .	1.094	. . .	. . .
				(2.12)		
LIV12 s_{ft}	. . .	. . .	−4.154	−3.971	. . .	.184
			(−1.22)	(−1.91)		(.08)
LIV12 s_{ft-1}	. . .	. . .	. . .	−7.256	. . .	. . .
				(−4.34)		
GAP_t	. . .	. . .	. . .	. . .	.485	.875
					(1.75)	(4.11)
Standard error of estimate	1.346	1.268	1.826	1.068	1.213	1.098
R	.919	.952	.844	.952	.942	.953
$\bar{R}^2$	.792	.830	.617	.879	.831	.861
Durbin-Watson	2.38	2.18	1.52	2.48	2.59	1.72

Sources: See table 17.5 and Gordon 1984a, table B-1 (GAP).

Note: t-statistics are in parentheses.

[a]GAP = (actual GAP − potential real GNP)/potential real GNP (%). Other symbols are defined in the text and in tables 17.4 and 17.5

[b]The dependent variable is the 3-month Treasury bill rate (TBR).

the same signs as their current-year counterparts, but they detract from the effects of the other variables and contribute but modestly to regression (6.2).

When F_t and s_{ft} are used instead of Φ_t and $s_{\phi t}$, coefficients with the same signs are obtained, but the t, R, and Durbin-Watson statistics are all lower (cf. eqs. [6.1] and [6.3]). The lagged terms F_{t-1} and s_{ft-1}, however, make relatively strong contributions (cf. eqs. [6.2] and [6.4]).

These results suggest that the joint effects of inflation expectations and uncertainty on i have been very strong in this period. Leaving out $\bar{s}_{\phi}$ or s_f and including instead DGE or DY (with or without lags) reduces the correlations greatly. The influence of DM_{t-1} turns out to be weak and ambiguous in its sign.

The evidence of equations (6.1)–(6.4) supports the proposition that inflation uncertainty σ influences i negatively, which is consistent with three of the recent papers that use the Livingston s_f data for the same purpose. (Two others report positive and one reports insignificant coefficients for the current and/or lagged values of s_f; see sec. 17.1.3.) A study by Lahiri, Teigland, and Zaporowski (1986), using $\bar{s}_\phi$-type data from the ASA-NBER surveys, finds positive effects that, however, are insignificant in the presence of selected "liquidity" and "exogenous demand" variables.[22]

When the percentage divergence of actual from potential real GNP (GAP) is added to the equation with current and lagged values of the LIV measures, its impact on TRB is revealed as positive and strong.[23] The addition of GAP_t diminishes the effect of DM_t and eliminates that of s_{ft} (cf. eqs. [6.3] and [6.6]). That the impact of s_f on TRB (as observed in earlier papers written or coauthored by Makin) disappears when GAP is included has been noted by Makin and Tanzi (1984, pp. 130, 134). In contrast to s_f, however, $\bar{s}_\phi$ retains its significantly large coefficient with a negative sign in the presence of GAP (cf. eqs. [6.2] and [6.5]).

The upshot is that the balance of the evidence, with more credence given to the probabilistic than to the point forecast data, favors the view that the effect of a rise in σ is to reduce i. As noted earlier, this implies that real investment is depressed more than real savings in the process. However, this result needs to be treated with caution since it could be quite sensitive to the choice of the time period covered and other specifications.

17.4 Conclusions

We define "consensus" as the degree of agreement among corresponding point predictions by different individuals and "uncertainty" as the diffuseness of the probability distributions attached by the same individuals to their predictions. To be useful the distinction must be made operational and measurable. The quarterly ASA-NBER surveys provide data on point and probabilistic forecasts of annual percentage changes in GNP and IPD, which can be applied to this task in several ways.

22. The authors pool the survey data across horizons and combine them with quarterly series for other variables. They use 3- and 6-month Treasury bill rates when the forecast horizon is two quarters or less and 12-month rates when it is three quarters or more; the two situations are also distinguished by means of dummy variables. The period covered is 1969:2–1985:2. Thus their study differs from ours in several respects, and it is not clear what accounts for the discrepancy in the results.

23. GAP is a cyclical factor, which is a broad measure of capacity utilization that affects real investment positively via an accelerator-type relationship (see Tanzi 1980; Makin and Tanzi 1984).

The matched mean point forecasts (F) and mean probability forecasts (Φ) agree closely. On the whole, then, the preferred predictions coincide with the expected values of the probability distributions assessed by the survey respondents.

Standard deviations of point forecasts (s_f) tend to understate uncertainty as measured by the means of standard deviations of predictive probability distributions ($\bar{s}_\Phi$), particularly for short horizons. The s_f series show much greater variability over time than the $\bar{s}_\Phi$ series, but the evidence suggests that these measures of consensus and uncertainty are for the most part positively correlated.

The s_f series derived from the semiannual Livingston survey forecasts have been widely used in recent literature as proxies for "inflation uncertainty." This practice receives direct support from our finding of substantial positive correlations between annual versions of these data and roughly consistent $\bar{s}_\Phi$ series of inflation based on ASA-NBER survey forecasts. However, matching the data from the two surveys presents small-sample and other measurement problems; hence the results of this analysis must be interpreted with particular caution.

Strong positive effects of Φ on $\bar{s}_\Phi$ for the rate of change in IPD (but not in GNP) provide evidence in favor of the hypothesis that expectations of higher inflation tend to generate greater uncertainty about inflation.

Real economic activity represented by the rate of change in constant-dollar GNP is adversely affected by a rise in inflation uncertainty measured by $\bar{s}_\Phi$, allowing for the influence of monetary growth and exogenous demand. The Livingston s_f data produce similar results, in this study and others.

A rise in uncertainty about inflation, other things equal, can either reduce or increase interest rates, depending on whether it depresses real investment more than real savings or vice versa. Studies using the s_f data have produced mixed results, interpreted accordingly. Our results indicate that a rise in $\bar{s}_\Phi$ on the average lowered the Treasury bill rate in the years 1969–81.