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ANALYZING THE RELATIONSHIPS BETWEEN SURVEY FORECASTS FOR DIFFERENT VARIABLES AND COUNTRIES

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This paper evaluates the quality of survey forecasts, their accuracy and unbiasedness, and their overall consistency. The paper also tries to find out whether the relationships between economic variables are the same in survey data and in the actual data. In other words we analyze whether the data generating mechanisms of forecast values and actual data coincide. The analysis deals with three countries/economic areas: the Euro Area, Japan and the US and makes use of different surveys and data frequencies. Since the results are somewhat blurred by the recent 2008-2010 financial crisis thus inclusion of the crisis period makes a lot of difference in main results. Even so, we find that the basic features of the data have quite few alarming features. Different surveys come quite close to each other and results for different countries/economic areas are reasonably similar. It is only that we find some evidence that the relationships between economic variables in the survey data are different from actual data. Moreover, we find that forecast errors are quite closely related to dispersion of survey respondents' forecasts. Thus, increased forecast uncertainty seems to be positively related to size of forecast errors.
Key words: Forecasting, Survey data, Phillips curve, Expectations

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Tarja Yrjölä has kindly derived and updated the data and Mika Kortelainen has provided useful comments.

1. Introduction

Expectations are known to be crucial determinants of economic outcomes being especially relevant for policy effectiveness. One can even go so far as to say that "all that matter is expectations". This importance shows up not only in economic models but also in efforts to measure expectations. Basically, we have three ways of handling expectations: (1) using the survey data, (2) deriving expectations from financial data and (3) relying on the Rational Expectations Hypothesis (REH) and using macro data within the GMM framework to produce proxies for expectations[1]. Little is still known of the relative performance of these three approaches (see, however, Ang et al (2007) and Kortelainen et

[1] Obviously, time series proxies may be constructed without postulating the REH – as was done when e.g. the adaptive expectations were used.

al (2011)). Even so, it is perhaps fair to say that the most often used REH & GMM approach has turned out to be less satisfactory being sometimes enormously sensitive to various details of the estimation procedure (see e.g. Adam and Padula (2010)). That clearly motivates use of survey data. Another motivating reason for using the survey data is the fact that these data provide a direct measure of expectations and allow for the analysis of the independent role of expectations in determination of various macro variables (see e.g. Paloviita and Viren (2009) and Canova and Gambetti (2010)). When using direct proxies of expectations, we do not have to assume that expectations are rational, or make any other assumptions of the way expectations are formed (e.g. adaptive, learning). A useful feature of at least survey measures is the availability of the original micro data (individual forecasters' responses) and thus a possibility to scrutinize both the disagreement between forecasters and the implied forecast uncertainty (say, in the form of standard deviation of individual forecasts), cf. e.g. Döpke and Fritsche (2006) and Dover et al (2009). Considering things like policy uncertainty, policy credibility and time consistency, these data are obviously immensely valuable (see e.g. Ball and Cecchetti (1990)).

Over time, survey measures have been used more frequently in testing economic models /hypothesis. Relatively little is known, however, on possible differences between these different measures and even less on relationships between these measures. Typically, expectations on a single variable, say inflation or real GDP growth, is analyzed at time. One may ask, however, whether the expectations on different variables in a survey x are internally consistent and whether these relationships are the same as in the data. In this paper we emphasize the latter property partly because things like accuracy and efficiency of forecasts are to some extent matters of taste. If the relationships between expectations on different variables are not the same as the corresponding relationships with the actual data we have hard time in interpreting expectations on individual variables.

This paper tries to shed light to these questions in scrutinizing data from different sources and different countries. More specifically, we focus on the US, the Euro Area and Japan, and within each economic area the main survey data sources such as the Livingston survey, the Bloomberg survey of forecasts, the Michigan survey, the Survey of Professional Forecasters, the ECB Survey of Forecasters and the Consensus Forecast data. In addition we have the OECD data which are available for USA, the Euro Area and Japan. The OECD data are not, of course, survey data but published "official" forecasts of OECD. However, these data cover all industrialized economies from the late 1970s and thus provide a useful benchmark for all comparisons. In addition to mean/media values of forecasts some survey measures also provide measures of forecast uncertainty (in the form of, say, standard deviations of forecasters' values). It is a challenging task to analyze whether these measures have some predictive power and whether these measures provide some information of the general public's interpretation of future course of economic policies (see e.g. Döpke and Fritsche (2006) , Lahiri and Sheng (2009) and Mankiw et al (2003) on analysis of disagreement of forecasts). The analyses in this paper are based on many different data sets (with somewhat different data frequencies) which contain real GDP growth and inflation for the three main countries/economic areas.

Although it is often challenging in large data sets like ours to find consistent results, to summarize them and interpret, a number of results emerge quite clearly from our analysis. Very briefly, the main result is that no major differences do seem to exist between different surveys and the surveys do seem to reflect the same relationships as actual (realized) data. The latter property is assessed using the Phillips curve relationship between output and inflation series as some sort of testing device. Using the Phillips curve as a frame of reference is obviously not completely innocent given the various pitfalls we may have in specifying, indentifying and estimating the Phillips curve (see e.g. Uhling (2010) for an exposition of this issue).

As for the structure of the paper, we first focus on the details of the data and the way in which comparable time series are constructed, then we carry out the empirical analyses and try to interpret the results and find out the novel features of the results. Finally, in section 4, we provide some conclusion and policy interpretations.

2. Details of the data

As mentioned above, the following six data sets are included in the subsequent analysis[2]:

The Bloomberg survey of forecasters (BL)
The Consensus Forecast (CF) data
The ECB Survey of Professional Forecasters (SPF:ECB)
The Survey of Professional Forecasters (SPF:USA)
The OECD forecasts (OECD)
The Michigan survey of consumers (MS) forecasts
The Livingston index (LI)

[2] The Bloomberg data are obtained from a set of 20-40 experts who express they views on future developments over the following four quarters. In a sense, the data are continuous but for the purpose of the current paper we have chosen the last month for every quarter. The Bloomberg data are exceptional in the sense that the data would allow an analysis of different forecast horizons (from one quarter to four quarters). In the ECB Survey of Professional Forecasters there are several forecast horizons (the current year and next two calendar years and also five years ahead). The US Survey of Professional Forecasters is the oldest quarterly survey of macroeconomic forecasts in the United States. The survey began in 1968 and was conducted by the American Statistical Association and the National Bureau of Economic Research. The Federal Reserve Bank of Philadelphia took over the survey in 1990. The Consensus Forecast data are provided by Consensus Economics that collects data from public and private economic institutions since October 1989. The data cover all major economies although for smaller countries the number of participating institutions is very small (preventing e.g. analyses on forecast uncertainty). With the US, the average number of respondents is close 30, with other major economic about 20. The data are monthly and provide values for the current and next calendar year developments of GDP and prices. The Livingston Survey was started in 1946 by the late columnist Joseph Livingston. It is the oldest continuous survey of economists' expectations. It summarizes the forecasts of economists from industry, government, banking, and academia. The number of respondents is about 48. The Federal Reserve Bank of Philadelphia took responsibility for the survey in 1990. The data are (currently) annual and semi-annual and include published forecasts for the current and next calendar year (or half-year). The Michigan survey of consumer expectations is conducted by the University of Michigan using telephone surveys to gather information on consumer expectations regarding the overall economy including consumer confidence and inflation on monthly basis. The survey also started in 1946. The number of respondent is about 600. OECD forecasts are made twice a year and cover the current and next calendar years (the December forecasts also cover the following calendar year). The data are available from the late 1970s.

The data are in most cases monthly although there are some exceptions. The Bloomberg data are quarterly while the Michigan survey and OECD data are semi-annual. The data represent the US (US), the Euro Area (EA) and Japan (J). In the case of Euro Area, the data are derived using a weighted average of Germany, France, Italy and Spain. A direct measure for the Euro Area is typically available only for the most recent years. We compared this "correct" Euro Area measure with the out weighted average measure and found that for the growth rates of output and prices the difference was negligible. With the dispersion measures, the difference was, of course, more pronounced and makes at least cross-comparisons more tedious. In our case, the Michigan survey and the OECD data are available since the beginning of the 1980s while the Consensus Forecast data and the Livingston index are from the beginning of the 1990s. The two shortest data sets, the ECB SPF and the Bloomberg data only cover the 2000s.

With almost all these forecasts/expectations we have the problem that forecast horizon is not fixed but the forecasts are provided for a fixed calendar period, usually the current and next calendar years; thus the survey data provides series of *fixed event* forecasts (the terminology comes Dover et al (2009)). However, we prefer *fixed horizon* (e.g., one-year-ahead) forecasts to allow all sorts of empirical tests. In addition, we use fixed horizon forecasts to provide results that are comparable to the literature. To approximate fixed horizon forecasts as a weighted average of fixed event forecasts we may use the following calculation rule (see Gerlach (2007) and Dover et al 2009 for details)). Denote $F[y_0,m,y_1(x)]$ the fixed event forecast of variable x for year y_1 made in month m of previous year, y_0 , and $F[y_0,m,12(x)]$ the fixed horizon, twelve-month-ahead forecast made at the same time. We can then approximate the fixed horizon forecast for the next twelve months as an average of the forecasts for the current and next calendar year weighted by their share in forecasting horizon:

$$F[\, y_0,m,12(x)] =((\, 12 - m\,)/12)* F[\, y_0,m,y_0(x)] + (m/12)* F[\, y_0,m,y_1(x)]. \quad (1)$$

For example, the July 2010 twelve-month-ahead forecast of inflation rate Δp $F[2010,7,12(\Delta p)]$ is approximated by the sum of $F[2010,7,2010(\Delta p)]$ and $F[2010,7,2011(\Delta p)]$ weighted by 5/12 and 7/12 respectively. We use this procedure for the three variables which are considered in empirical analysis: the Gross Domestic Product (GDP) growth rate, the inflation rate and the unemployment rate. Inflation is here defined in terms of both the Consumer Price Index (CPI), consumer prices PC (which is the implicit price deflator of private consumption) and the implicit GDP price deflator (DEF)). As for the CPI, we have both the national definition of CPI (CPI) and the (European Union) harmonized consumer price index (HICP). In addition, we have data for the unemployment rate (UR).

3. Interpretation of results

Now, turn to empirical results. They are reported as follows: In Figure 1, we show the main time series of GDP and inflation expectations for the three countries/economic areas. Both the actual (not real-time) and forecast values are displayed. In addition to time series of mean values of expectation we also show dispersion measures for the surveys which provide the measures directly or allow for computing the deviations between individual forecasters[3].

In Table 1, we report the values of main forecast accuracy statistics, the Mean Error (ME), the Mean Square Error (MSE) and the Mean Absolute Error (MAE). Then in Table 2, we show the F-test statistics for the traditional unbisedness tests (that is the test for the hypothesis a=0 & b=1 in regression between actual (A) and forecast (F) values: A = a+ bF). Finally, in Table 3, we report correlation coefficients between inflation and real output growth for, on the one hand, actual data and, on the other hand, for the forecast values. The idea of this exercise is to examine whether the data generating mechanism of the forecasters is roughly the same as with the whole economy (i.e. realized data). In addition to correlation coefficients, we compute estimates for the following simple backward-looking Phillips curve (see Table 4):

$$\Delta^2 p = \alpha(y - y^*), \qquad (2)$$

where $\Delta^2 p$ denotes the second backwards differencing of the price level (see Fuhrer et al (2010) for motivation of this equation). Equation (2) is estimated both for the actual data and for the survey expectations' data to see where the same structure exists in the both data generating mechanisms. Finally, the analysis is accompanied by a comparison of (correlations between) forecast errors between GDP growth and inflation as well as comparison for forecast uncertainty measures. These results are reported in Tables 5 and 6.

Turn now to the main results and start with results dealing with forecast accuracy and unbiasedness (see Tables 1 and 2). As for these statistics, our results appear to be rather interesting in the sense that no major differences appear between different data sets in spite of different surveys, countries, sample periods and data frequences. In it noticeable that OECD forecasts do not seem to deviate from survey numbers. Some interesting features can be found in both inflation and output growth expectations. In both cases, the survey values are quite persistent so that changes inflation and output growth are relatively poorly predicted. Thus it takes quite a long time before agents seem to realize that there has been a major slump in output or acceleration in growth (see Isiklar et al (2006) for an analysis of inflation expectations dynamics). As for inflation, the survey values seem to be systematically above the realized data perhaps reflecting the fact that agents have not fully internalized the great moderation in inflation (see Stock and Watson (2007) for more thorough analysis). Bias in inflation is so systematic that the Rational Expectations Hypothesis is rejected for almost all surveys.

As for Table 3, one may conclude that correlations between actual, on the one hand, and forecast variables, on the other hand, are qualitatively quite similar although in the case of Japan (see the two first lines of Table 3) the difference is significant. Things become quite different, however, when we focus on the sample before the recent financial crisis. Then, more differences arise (see the Euro Area numbers for SPF and OECD) and Bloomberg numbers for the US. It is also worthwhile to point out that the pre 2008 and data and the whole data see to produce very different numbers, especially for the U.S.

[3] The ECB Survey of Professional Forecasters would include confidence bands for individual forecasts but here we do not use these values because we have no obvious counterpart to them among other surveys.

Estimates of the backward-looking Phillips curve (2) in Table 4 give a bit clearer difference between actual and survey data although different surveys and with different sample periods make still a lot of difference to the results. With only the ECB SPF data, the coefficient of the output is significant (and positive) while with all other survey data, as well as with the OECD data, the Phillips curve relationship does not exist even though the actual data seem to follow that pattern (the statistical power of this conclusion is not very strong, however). With the Bloomberg data the evidence remains a bit moot due to rather short sample period. Thus there appears to be a difference between the actual and survey data in terms of the relationships between variables possibly reflecting different data generating mechanisms. All in all, the results suggest that with actual data a Phillips curve type relationships seems to exit but with the survey data it cannot be identified at all (or the slope is of wrong sign).

As for forecasts errors (Table 5), the perhaps most striking result concerns the difference between the OECD forecasts for Europe and Japan, on the one hand, and USA, for the other hand. The relationship appears to be negative for the US which cannot be se easily explained. Similar result – again with the US - is detected with the pre 2008 data also with the Consensus Forecast data.

It is interesting to compare the correlations of forecast errors (reported in Table 5) with correlations between forecast errors and forecast dispersions (that is, standard deviations of different respondents' expectation). These latter correlations are displayed in Table 6. Moreover, the corresponding scatter-plots are shown in Figure 2. As for forecast errors, we also show both absolute and nominal values of the errors.

The results are interesting in suggesting that forecast uncertainty (dispersion of individual forecasts) is positively related to size of forecast errors, and that dispersion of CPI and GDP forecasts are positively related. The latter result most obviously reflects a Phillips curve type relationships between these two variables: high values of GDP are related to high values of inflation and vice versa. As for the forecasts errors, we may conclude that if opinions of the future course of events differ a lot then also the recorded survey numbers tend to be wrong more often that in the case where all respondents have the same view. Correlations also suggest that forecast uncertainty is negatively related to actual (not absolute values of) forecast errors. Thus, if dispersion of forecasts is large the forecast values tend to be higher than the realized values. That could be interpreted as some sort of "optimism bias", or maybe it just reflect the fact that with a lot of forecast uncertainty the best guess is the set of steady state values. Thus, severe depressions come always as a surprise.

As for the correlation of inflation and output growth uncertainties, the values are quite low even though they are positive (Figure 3). Moreover, there are some obvious differences between different surveys. Thus, with the Consensus Forecast data, the Euro Area and the US figures show relatively clear positive association but with Japan such feature is hardly visible. The Livingston and SPF(USA) surveys also show very weak association between these two dispersion measures. The nature of Japanese figures is a bit puzzling because both the actual and expected inflation and output growth seem to quite strongly correlated just in Japan (Table 3).

One caveat needs to be pointed out, however. The uncertainty (dispersion) measures are not very robust judging from the fact that they are much weakly correlated than the mean forecasts. Thus, for instance, correlation between the standard deviations of Consensus Forecast and Livingston survey is 0.526 for output growth and 0.575 for inflation while correlation coefficient between mean forecasts are 0.730 and 0.802, respectively. Comparable correlation coefficients between the dispersion measures of Consensus Forecast and SPF(USA) are 0.472 and 0.499 and finally between SPF(USA) and the Livingston survey are 0.455 and 0.272. With European data, we find similar values. Thus the correlation between the inflation dispersion measures of Consensus Forecast and SPF(ECB) is only 0.257. The numbers differ from zero but relatively low values suggest that uncertainty measures are far from identical and may include large measurement errors[4].

4. Conclusions

Our analyses show that there are no striking differences between different survey results in terms of accuracy and unbiasedness across different counties and alternative surveys. All forecasts seem to be quite persistent so that changes in growth rates of inflation and output are only poorly predicted and, hence, the rational expectations hypothesis is not supported by the data. When we scrutinize the structure of the data some interesting features can be detected. There is a systematic, although statistically weak, difference between actual data and forecast data. Thus, inflation and output growth appear to be positively correlated with the actual data but not the forecast data. Even more striking difference emerges with simple Phillips curves: with the forecast data the slope is typically negative! The results with forecast uncertainty (with is proxied with the dispersion of survey forecasts) and forecast errors are perhaps even more interesting. Inflation and output growth forecast dispersions are strongly correlated with each other and they are also positively correlated with (abosolute) forecast errors. Dispersion of forecasts can therefore be used as proxies for confidence intervals of forecast values.

There are several caveats, however. Some of the results seem extremely sensitive in terms of the sample period, especially the inclusion of the recent financial crisis. This, this crisis was not predicted and the very large prediction errors easily dominate the results for the whole sample. One may also doubt whether the different surveys are representative from point of view of the general public and whether different surveys are completely independent. Survey results are published regularly and that may affect the answers of the respondents of other competing surveys. In principle, we could find out how strong this contagion effect is by scrutinizing the publication and interviewing dates if different surveys but that is really beyond the scope of this paper.

Another caveat is relation to the relationships between different forecasts: it is quite probable that at least economists follow different survey results and thus it is not all clear to what extent the expressed values reflect own independent information instead of reproduction of published other forecasts and surveys.

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[4] Comparing the dispersion measures is not easy because of different frequencies and the fact that the SPF surveys uses the 75th percentile minus the 25th percentile of the forecasts as the dispersion measure.

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Table 1

Forecast accuracy statistics

Data	Euro Area			Japan			USA		
	ME	**MSE**	**MAE**	**ME**	**MSE**	**MAE**	**ME**	**MSE**	**MAE**
CF:GDP	-0.373	1.528	0.894	-0.532	3.448	1.352	-0.061	1.831	1.077
CF:CPI	-0.082	0.248	0.378	-0.123	0.322	0.453	-0.039	0.651	0.620
SPF:GDP	-0.377	2.923	1.203				0.095	2.012	1.127
SPF:HICP	0.141	0.476	0.469				-0.321	0.928	0.770
SPF:UR	-0.012	0.545	0.534						
OECD:GDP	-0.306	1.791	1.034	-0.269	3.618	1.331	0.200	2.135	1.185
OECD:PC	-0.486	0.981	0.763	-0.395	0.638	0.631	-0.309	0.850	0.726
OECD:DEF	-0.438	0.707	0.645	-0.634	1.123	0.834	-0.309	0.746	0.696
BL:GDP							-0.912	1.947	1.041
BL:CPI							0.063	1.096	0.736
LI:GDP							-0.143	3.407	1.402
LI:CPI							-0.081	1.028	0.787
MS:CPI							0.112	1.375	0.813

The sample periods for Bloomberg is 2000Q1-2010Q2, for Consensus Forecasts 1990M11-2010M3, for the Surveys of Professional Forecasters 2000Q1-2010Q2, for OECD 1981S2-2009S2 and for Michigan survey 1979M1-2010M7.

Table 2

Test for unbiasedness

	Euro Area	Japan	USA
CF:GDP	0.067	0.021	0.891
CF:CPI	0.032	0.245	0.093
SPF:GDP	0.702		0.778
SPF:HICP	0.066		0.001
SPF:UR	0.000		
OECD:GDP	0.455	0.675	0.575
OECD:PC	0.000	0.000	0.000
OECD:DEF	0.000	0.001	0.000
BL:GDP			0.000
BL:CPI			0.052
LI:GDP			0.631
LI:CPI			0.001

Values are marginal significance levels of the F -test statistic.

Table 3

Correlation coefficients between GDP and inflation

	Euro Area	Japan	USA
	whole data		
CF: actual	0.182	0.303*	0.194
CF: exp	0.259	0.713*	0.067
SPF: actual	0.497		.047
SPF: exp	0.524		-.021
OECD: actual PC	0.129	0.511	-0.049
OECD:exp PC	-0.166	0.720	-0.198
OECD: actual DEF	0.051	0.459	-0.148
OECD:exp DEF	-0.184	0.600	-0.238
BL:actual			0.636
BL: exp			0.402
LI: actual			0.414
LI: exp			-0.058
	prior to 2008		
CF: actual	-0.147	0.286*	-0.402
CF: exp	-0.020	0.782*	-0.550
SPF: actual	-0.396		-0.296
SPF: exp	0.031		-.213
OECD: actual PC	-0.074*	0.464*	-0.257
OECD:exp PC	-0.493*	0.740*	-0.436
OECD: actual DEF	-0.107*	0.470	-0.345
OECD:exp DEF	-0.486*	0.683	-0.439
BL: actual			0.423
BL:exp			-0.023
LI: actual			-0.061
LI: exp			-0.389

Starred coefficient are statistically (with 5 per cent level of significance) different. In the lower panel, correlation coefficients that differ from the corresponding full sample coefficients are expressed with bold fonts.

Table 4

Estimates of a backward-looking Phillips curve with actual and survey data

	Euro Area	Japan	USA
CF: actual	0.062	0.019	0.006
	(2.09)	(2.81)	(1.36)
CF: exp	0.001	0.006	0.004
	(0.33)	(1.12)	(0.98)
SPF: actual	0.062		0.018
	(2.09)		(1.60)
SPF: exp	0.043		-0.011
	(2.13)		(1.20)
OECD: actual PC	0.014	0.027	0.011
	(0.26)	(0.84)	(0.51)
OECD:exp PC	-0.021	-0.32	-0.012
	(0.52)	(0.10)	(0.50)
OECD: actual DEF	-0.012	0.011	-0.002
	(0.04)	(0.47)	(0.12)
OECD:exp DEF	-0.024	-.012	-0.024
	(0.70)	(0.49)	(1.01)
BL:actual			-0.073
			(1.53)
BL: exp			0.051
			(1.62)
LI:actual			.068
			(1.17)
LI:expected			-.008
			(0.81)

Numbers are coefficient estimates and (inside parentheses) t-ratios of coefficient α.

Table 5

Correlation coefficients between forecast errors

	Forecast errors		
	whole data		
variables	Euro Area	Japan	USA
CF: GDP, CPI	0.396	0.310	0.073
SPF:GDP,HICP	0.607		-0.066
OECD: GDP, PC	0.203	0.233	-0.033
OECD:GDP, DEF	0.041	0.080	-0.244
BL:GDP, CPI			0.598
LI: GDP,CPI			0.091
	prior to 2008		
CF: GDP, CPI	0.162	0.245	-0.294
SPF: GDP, HICP	0.125		-0.172
OECD:GDP, PC	0.144	0.146	-0.062
OECD: GDP, DEF	0.027	0.056	-0.252
BL:GDP; CPI			-0.131
LI: GDP, CPI			-0.291

Table 6

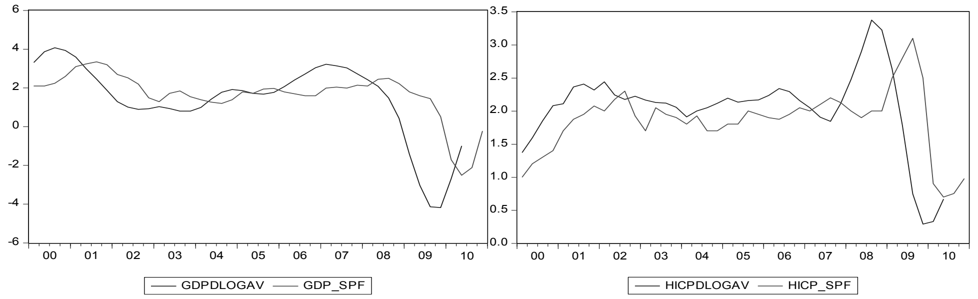
Correlation between forecast dispersion and forecast errors

	SDCPI& SDGDP	**SDCPI&ECPI**	**SDCPI&AECPI**	**SDGDP&EGDP**	**SDGDP&AEGDP**
Euro Area	0.637	-0.296	0.031	-0.215	0.291
Japan	0.292	-0.144	0.195	0.036	-0.047
USA	0.563	-0.212	0.299	-0.185	0.087

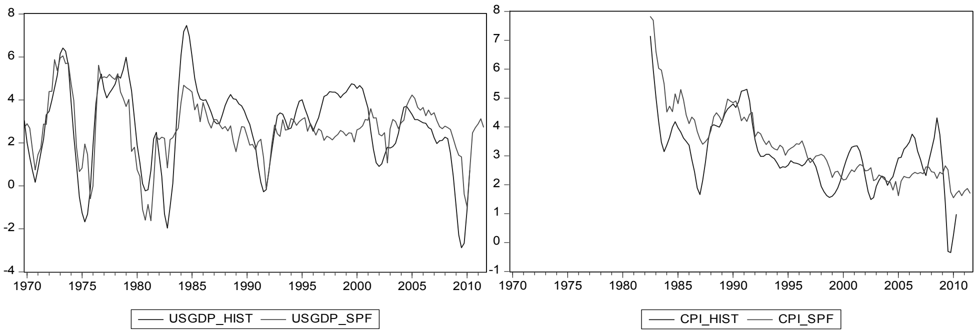
The 5 per cent critical value is 0.138.

Figure 1 Actual and forecast values for GDP and inflation in different surveys

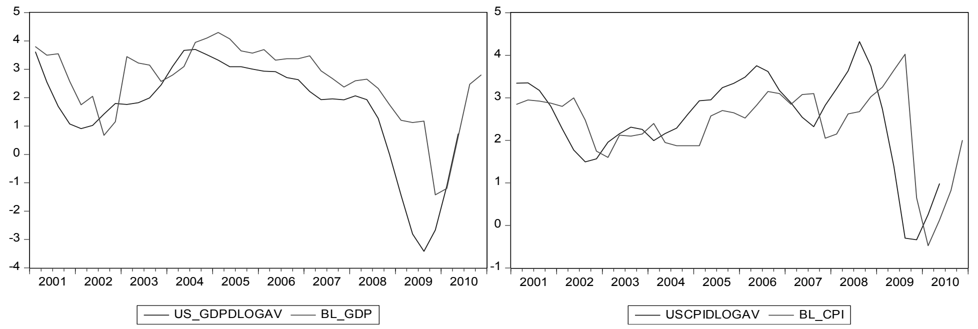
Euro Area: SPF



USA:SPF



USA:BL

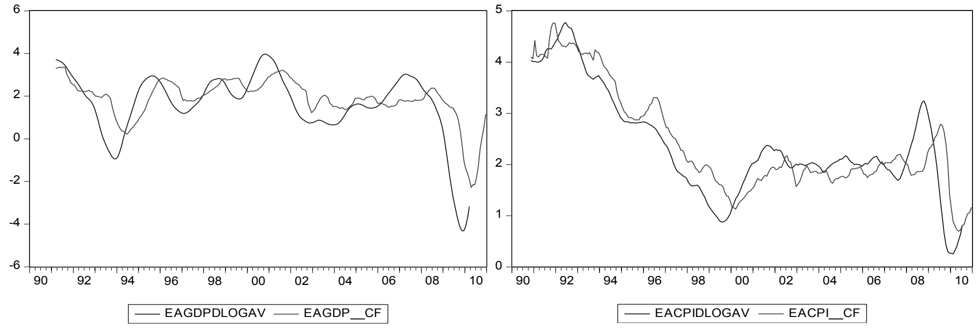


USA: Livingston

Figure 1 continued

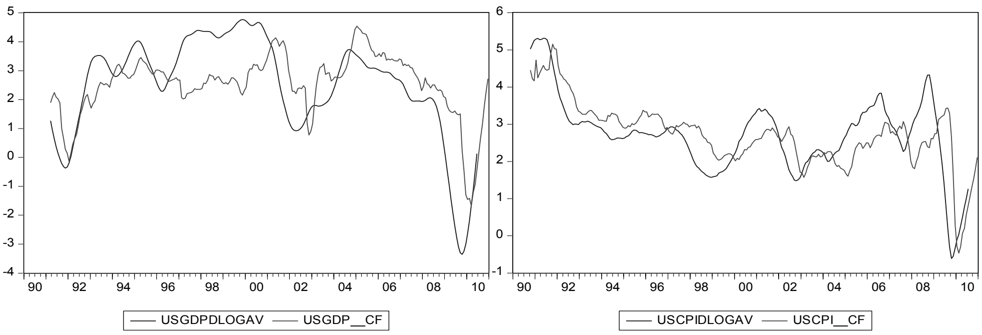
Consensus Forecast data

Euro Area



Japan

USA

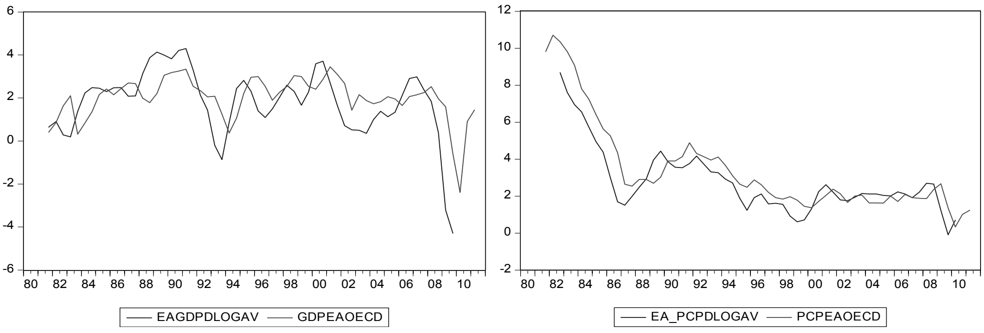


The abbreviation follows the syntax: country name_GDP growth (of CPI inflation)_actual data(dlogav)/forecast data(_CF).

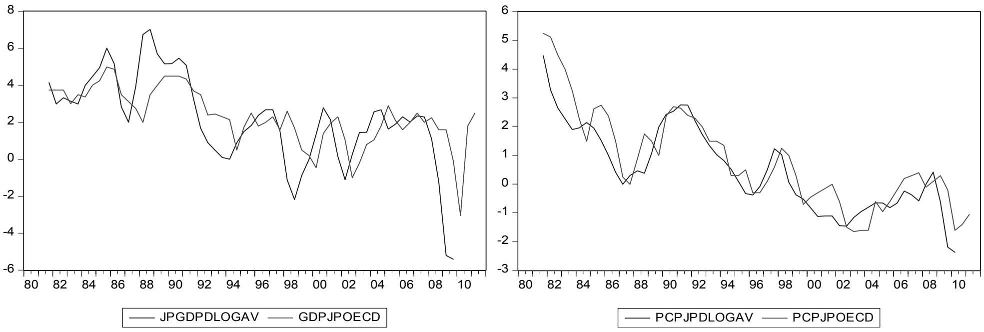
Figure 1 continued

OECD data

Euro Area



Japan



USA

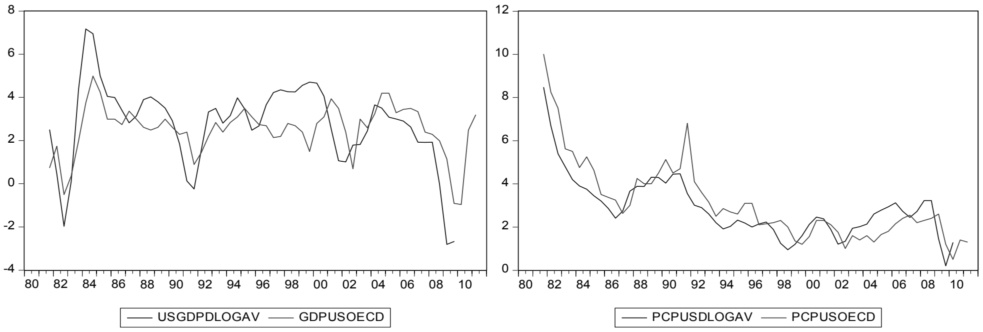
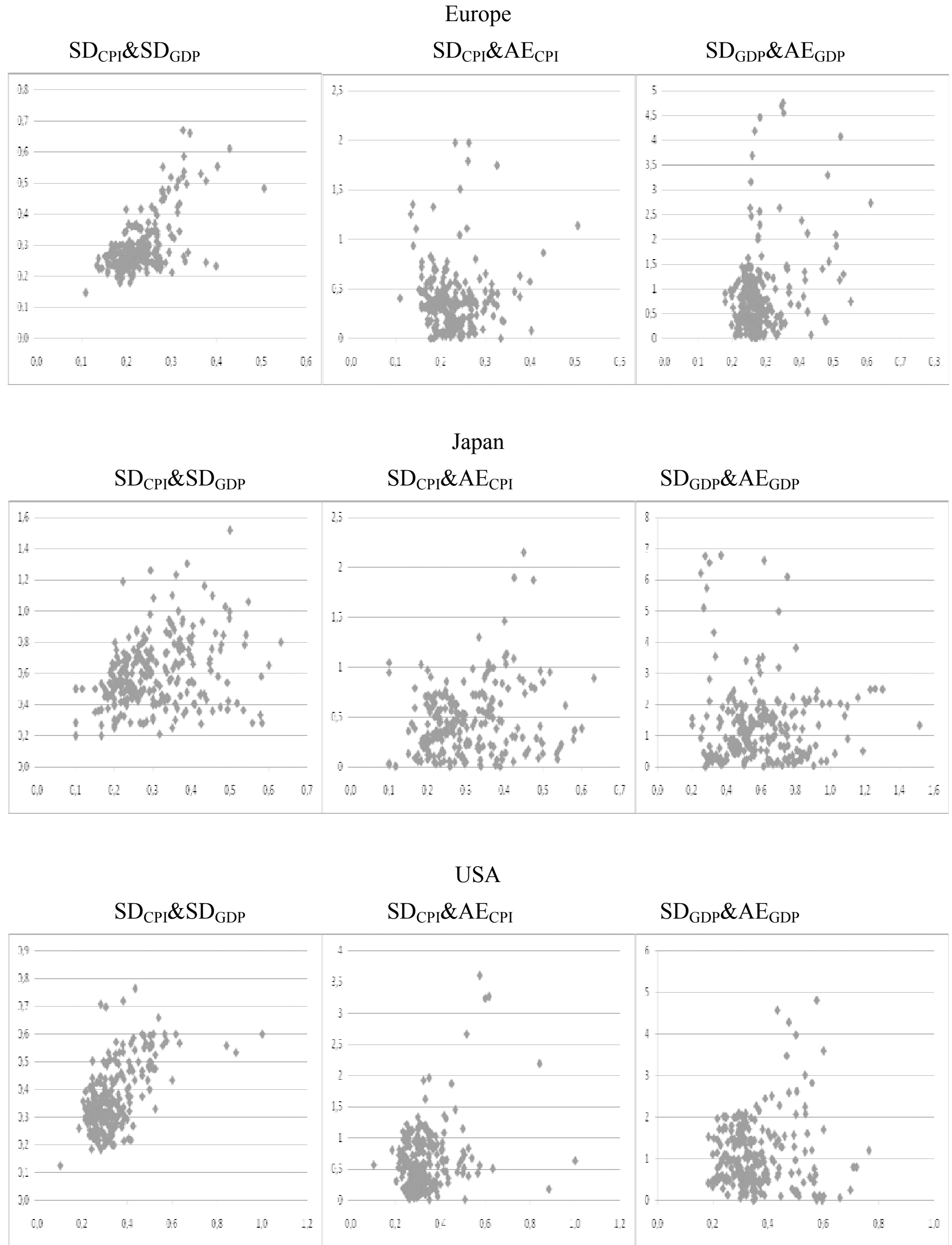


Figure 2 Indicators of forecast uncertainty

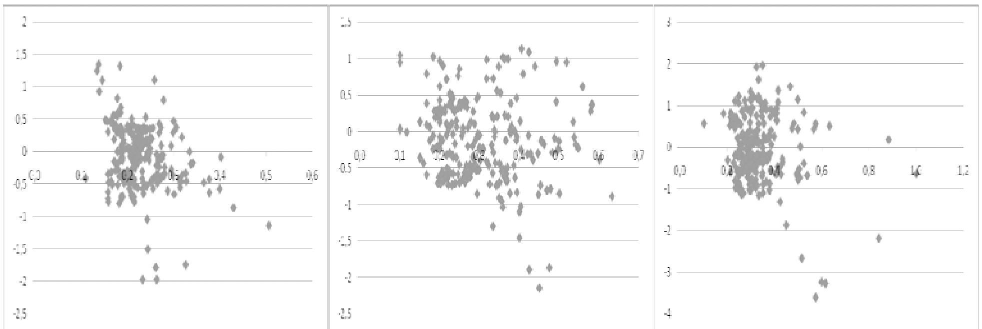


SD denotes standard deviation of CF forecasters' reponses (x-axis) and E (AE) (absolute) forecast errors (y-axis).

Figure 2 Indicators of forecast uncertainty continued

Europe Japan USA

SD_{CPI}&E_{CPI} SD_{CPI}&E_{CPI} SD_{CPI}&E_{CPI}



SD_{GDP}&E_{GDP} SD_{GDP}&E_{GDP} SD_{GDP}&E_{GDP}

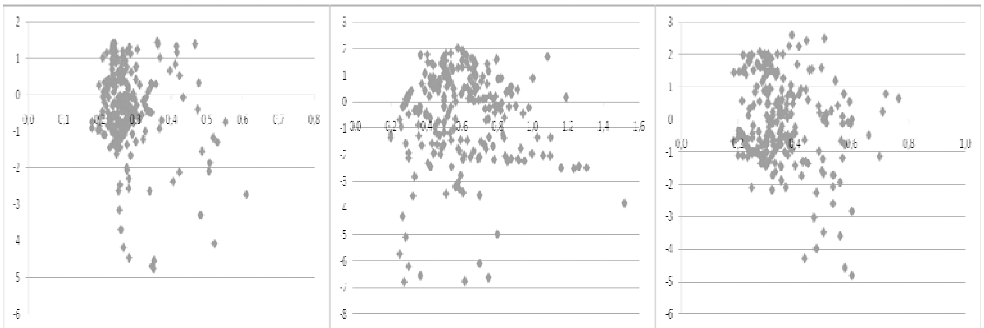
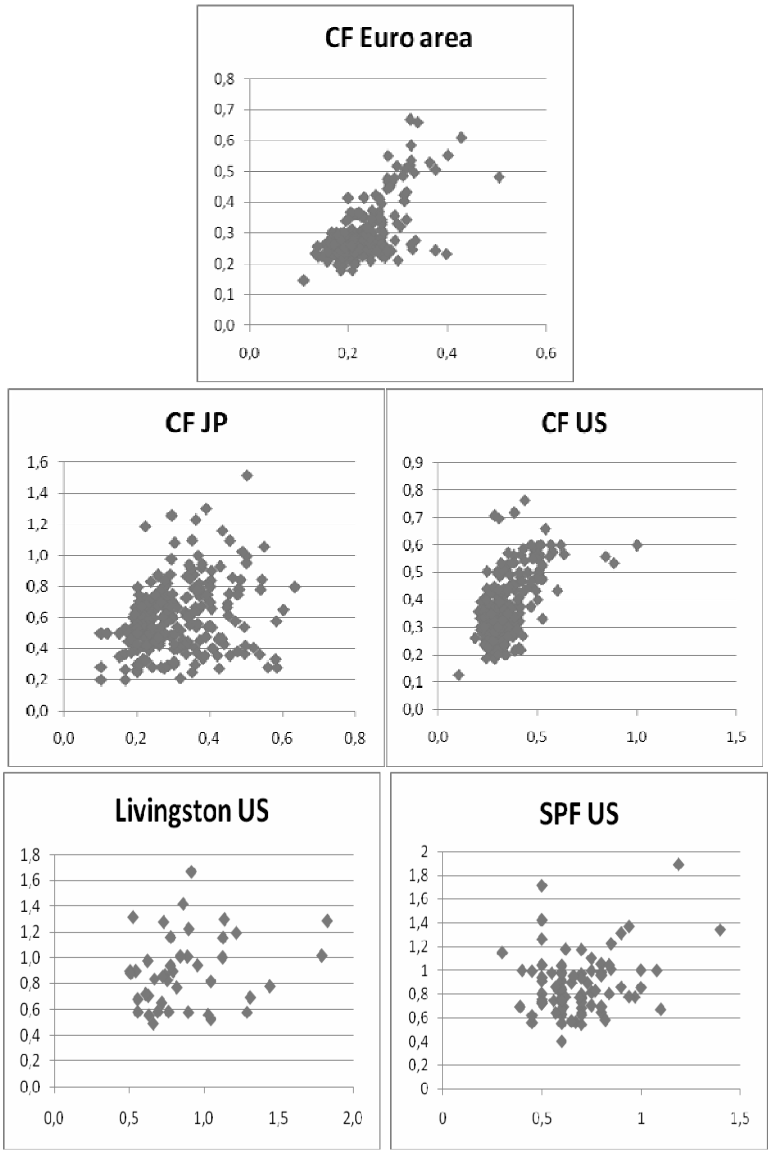


Figure 3 Relationship between inflation and output growth uncertainty



Inflation uncertainty in x-axis and output growth uncertainty in y-axis. The respective correlation coefficients are: CF:EA 0.64, CF:JP 0.29, CF:US 0.56, LI:US 0.21 and SPF:US 0.13. The two last are not statistically significant at the 5 per cent level of significance.