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Data Dissemination Standards and the Statistical Quality of the IMF's World Economic Outlook Forecasts

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Data Dissemination Standards and the Statistical Quality of the IMF's World Economic Outlook Forecasts[1]

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Abstract

This paper analyzes the effects of IMF member countries participation in the IMF's Data Standards Initiatives (DSI) on the statistical quality of WEO forecasts. Results show that WEO forecasts for SDDS subscribers are in general better than for GDDS participants and those member countries than do not participate in the DSIs. Policy implications are that the DSI positively affect the statistical quality of forecasts and by extension improve the necessary conditions for multilateral surveillance and the provision of member countries with high quality policy advice.

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Contents Page

Tables

Figures

I. INTRODUCTION

This paper analyzes the effects of IMF members' participation in the IMF's Data Standards Initiatives (DSI) on the statistical quality of World Economic Outlook (WEO) forecasts. IMF member countries participating in the DSI are either subscribers to the Special Data Dissemination Standard (SDDS) or participants in the General Data Dissemination System (GDDS). Both SDDS and GDDS are of importance in development and dissemination of good quality macroeconomic and socioeconomic data, but they differ in their periodicity and timeliness requirements. The first hypothesis tested in this paper is that the statistical quality of WEO forecasts for SDDS subscribers is superior to that of GDDS participants and countries that do not participate in the data dissemination standards. The second hypothesis is that the differences in the statistical quality of forecasts are greater for those data categories that are disseminated more frequently and/or timelier in SDDS than they are in GDDS.

Existing analyses of the effects of the data dissemination standards have focused on the market efficiency effects of the standards on the cost of borrowing by Cady (2005) and Cady and Pellechio (2006) and on the volatility of exchange rates Cady and Gonzalez-Garcia (2006). To our knowledge, there have been no studies of the effect of the IMF's data standards on the statistical quality of WEO forecasts. This paper is intended to fill this gap by analyzing the relationship between data dissemination standards and the statistical quality of the WEO forecasts for the IMF's member countries.

The WEO is one of the main forecasts of global economic activity; it is published twice a year in Spring and Fall and includes forecasts of the key macroeconomic variables for the IMF's member countries and for country groups.[2] Several studies have evaluated the statistical quality of the WEO forecasts and looked for ways to improve them. Examples include Artis (1996), Barrionuevo (1993), Artis (1998) and Timmerman (2005).

The present study builds on Timmerman (2005), but deviates from his analysis in four ways. First, it computes the summary statistics of WEO forecasts for real GDP growth and inflation for the period 1999-2007 conditional on participation/subscription to GDDS and SDDS respectively. Second, it performs statistical tests to determine the effects of participation in IMF's data standards on the statistical quality of WEO forecasts. Third, it studies unconditional and conditional correlations of intra and inter-temporal WEO forecast errors to obtain estimates of the statistical quality of the forecasts regarding their underlying economic structure. Finally, the statistical analysis uses is not based on time series but rather on cross section properties of forecast errors.[3]

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[2] In this paper, we focus on the analysis of the current period and next period forecasts.

[3] This choice results in different statistical significances; the present analysis finds fewer cases of bias than that conducted by Timmernan. The reason for this difference is pooling of forecast errors across countries.

The paper is organized as follows. Section 2 describes the timing conventions of WEO data, summarizes the theoretical properties of optimal forecasts and explains the key statistical properties of optimal forecasts. The Section also describes different periodicity and timeliness requirements of the SDDS and the GDDS and explains why those different requirements could potentially affect the statistical quality of WEO forecasts. Section 3 describes the data set, including coverage by years and by regions and presents descriptive statistics. The Section also describes a parsimonious parametric model of forecast errors and shows that they are not normally distributed. This finding plays an important role in the selection of statistical tests subsequently used in the paper, as the tests must be robust deviations from the normal distribution. Statistical properties of tests that are used in the paper are described in the Appendix. Section 4 presents the results of the empirical analysis and Section 5 concludes.

II. A THEORETICAL PRELUDE

A. Timing conventions

For purposes of compatibility and comparison with existing research, the timing conventions in this paper correspond to those in Timmerman (2005). Because the reported variables are subject to revision, a choice has to be made concerning the vintage of actual data to use to measure realized values or outcomes. We follow common practice and use the first-available data in the Spring WEO issue of year t + 1 to measure the outcome of the predicted variable in period t (labeled x_t) while next-year forecasts for period t + 1 are compared to the realized values for year t + 1 (x_{t+1}) reported in the Fall WEO issue of year t + 2.

There are two sets of current year forecasts generated in Spring and Fall respectively, $\hat{x}_{t,t}^{Spring}$ and $\hat{x}_{t,t}^{Fall}$. In addition, there are two sets of next-year forecasts generated during the same periods and labeled $\hat{x}_{t+1,t}^{Spring}$, and $\hat{x}_{t+1,t}^{Fall}$. The first subscript indicates the period being predicted while the second subscript indicates the year when the forecast was generated. The superscript indicates the period of the WEO issue where the WEO forecast was reported. Using this convention, we define the following four forecast errors.

Spring current year forecast error

$$e_{t,t}^{Spring} = x_t - \hat{x}_{t,t}^{Spring}. \tag{1}$$

Fall current year forecast error

$$e_{t,t}^{Fall} = x_t - \hat{x}_{t,t}^{Fall}. \tag{2}$$

Spring next year forecast error

$$e_{t+1,t}^{Spring} = x_{t+1} - \hat{x}_{t+1,t}^{Spring}. \tag{3}$$

Fall next year forecast error

$$e_{t+1,t}^{Fall} = x_{t+1} - \hat{x}_{t+1,t}^{Fall}. \tag{4}$$

B. Properties of Optimal Forecasts

Diebold and Lopez (1995) state the four key properties of optimal forecasts:

1. optimal forecast errors have a zero mean, that is, they are unbiased;
2. 1-step-ahead optimal forecast errors are white noise;
3. k-step-ahead optimal forecast errors are at most MA(k-1);
4. k-step-ahead optimal forecast error variance is non-decreasing in k.

A direct consequence of the fourth property of optimal forecasts is a decreasing variance forecast errors. Intuitively, optimal forecasts that use more information should have smaller conditional variance than those using less information. Spring WEO forecasts for the current year should have greater variances than Fall WEO forecasts for the same year because Fall forecasts are conditional on more information than Spring forecasts. Mathematically this statement is expressed as

$$\mathrm{Var}\left(e_{t+1,t}^{Spring}\right) \geq \mathrm{Var}\left(e_{t+1,t}^{Fall}\right). \tag{5}$$

The covariance structure of optimal multivariate forecast errors of economic variables possesses some important properties which should be used to analyze the statistical quality of forecasts.

Second, there might be nonzero intra-temporal correlations between forecast errors of different economic variables due to common aggregate shocks. Therefore, it is not required that the intra-temporal correlations between forecast errors of different economic variables equal zero. Both conditions in equation (6) are permissible for optimal forecasts.

$$\begin{aligned} &\mathrm{Cov}\left(e_{t+k,t}^{Spring,GDP}, e_{t+k,t}^{Spring,\pi}\right) \neq 0, \quad k \in \{0,1\} \\ &\mathrm{Cov}\left(e_{t+k,t}^{Spring,GDP}, e_{t+k,t}^{Spring,\pi}\right) = 0, \quad k \in \{0,1\} \end{aligned}. \tag{6}$$

C. Data Dissemination Standards and Forecast Statistical quality

The IMF's data dissemination standards, GDDS and SDDS, impose requirements on the periodicity and timeliness of dissemination of macroeconomic and socio-economic data. Broadly speaking, the SDDS in most cases requires higher frequency (periodicity) and less delay in data dissemination than the GDDS. An illustrated example of timeliness and periodicity differences between the two data standards is in Figure 1.

Based on the differences in frequency and timeliness of data dissemination between SDDS and GDDS we can state the following hypothesis. Unbiased forecasts of macroeconomic variables that are disseminated by SDDS subscribers should have smaller variances than unbiased forecasts of macroeconomic variables that are disseminated by GDDS participants only if SDDS periodicity and timeliness requirements are stricter than GDDS requirements.

Let us consider two examples. First, real GDP forecasts for SDDS subscribers should have smaller variances than real GDP forecasts for GDDS participants, because the SDDS requires quarterly dissemination with a quarterly lag and the GDDS only requires annual dissemination of national accounts data. Second, one should not expect significant differences in the variances of inflation forecasts, because both the SDDS and the GDDS require dissemination of inflation data with monthly periodicity and monthly timeliness.[4]

III. The Data Set

The data set consists of the Spring and the Fall WEO real GDP growth rates and CPI inflation rates forecasts for the period 1999-2007. The forecast errors have been computed as described Section II. To reduce the possibility of outliers affecting the results of the analysis, we dropped variables with values, which are considered extreme and are for all practical purposes extremely difficult if not impossible to forecast. Specifically, we dropped all observations where the realized absolute value of the real GDP growth exceeded 15 percent per annum. Similarly, we dropped all observation where the realized CPI inflation rate exceeded 200 percent per annum. In addition, the third WEO of year 2001 is excluded due to its one-off nature—the third 2001 WEO was issued to present the expected economic consequences of the 9/11 attacks. Finally, data on those countries that did not exist for the entire period of observation have been omitted.

A. Data Coverage by Year and by Region

Table 1 presents some information on data coverage within each of the years for the analyzed variables. A minimum of 170 observations is available for year 1999 and a maximum of 349 for year 2007. Country coverage after 2002 nearly complete; the database contains two observations per annum for approximately 180 member countries. The coverage for the period 1999-2002 was significantly less comprehensive than for the period from 2002 onwards due to less complete coverage of developing countries in the former period. The

[4] If variables other than lagged inflation rates, for example real GDP growth or the output gap, are used in forecasting inflation, then unbiased forecasts for SDDS subscribers could have smaller variances than unbiased forecasts for GDDS participants due to higher dissemination frequency of the covariates used in forecasting inflation.

table also shows the mean and standard deviations of forecast errors for both real GDP growth and inflation forecasts.[5]

Table 2 presents some information on data coverage for broad geographic regions. The number of observations per region ranges from 422 for Region 2 to 677 for Region 3. The number of all observations exceeds two thousand. The sample size is large enough that the results of asymptotic statistical analysis can be used with confidence at least for the sample means and that small sample corrections (such as bootstrap methods) are not necessary.

B. Descriptive Statistics of Forecast Errors

Table 3 presents the summary statistics of the analyzed forecast errors. Some conclusions are readily apparent. First, none of the forecast errors is statistically significantly different from zero– their t-values are well below any standard critical values. In other words, the forecasts are unconditionally unbiased. Second, three out of four forecast errors have skewed (asymmetric) distributions, which is evidenced by the large (negative) values of the sample skewness estimates. In addition, all forecast errors have fat tails. The kurtosis of the normal distribution is equal to three. All variables in the table have kurtosis values that greatly exceed three, which indicates fat tails. Third, the null hypothesis of normality is strongly rejected in all cases by the Jarque-Berra test statistic. The p-values for the Jarque-Berra test statistics are equal to zero to four decimal places for all test statistics. Fourth, same period forecast errors have lower standard deviations than one period ahead forecast errors.

C. The Distribution of Forecast Errors

An interesting albeit not crucial empirical issue is to determine the distribution of the analyzed forecasting errors. Figure 2 compares the kernel estimate of the sample density of the real GDP growth same period forecasting error with its parametric estimate under the assumption of normality.[6, 7] The empirical density strongly differs from normality: it has a higher value at the mode and fatter tails. Empirical evidence shows that the most suitable parametric family is the four-parameter Pearson family of probability distributions. This four-parameter family of distributions is much richer than the distributions that we usually encounter in empirical work.

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[5] Timmerman deleted missing observations where the forecast is identical to the realized value. The present analysis does not delete those cases where the forecast and the realized value are identical, since to our understanding there is no need to delete perfect forecasts.

[6] Epanechnikov (quadratic) kernel was used in the analysis and the bandwidth was automatically selected by Eviews 6.0. Other choices of kernels gave very similar results.

[7] Other forecasting errors exhibit similar properties; they are strongly non-Gaussian.

The Pearson density is defined as any valid solution to the linear differential equation $\frac{\mathrm{p}'(x)}{\mathrm{p}''(x)} = \frac{x-\lambda}{b_2(x-\lambda)^2 + b_1(x-\lambda) + b_0}$ whose solution is $\mathrm{p}(x) \propto \exp\left(-\int \frac{x-\lambda}{b_2 x^2 + b_1 x + b_0} dx\right)$.

Based on the sign of the discriminant and the restriction on the signs of the roots one can classify the members of the Pearson family into the seven different types, some of which are reducible to standard probability distribution, for example the normal distribution.

Results of parametric estimation are presented in Table 4. We see that forecast errors of the same period and one period ahead real GDP cannot be reduced to standard probability distributions. The probability density of the same period inflation forecast error is four-parameter beta distribution and the probability density of the one period ahead period inflation forecast error is F-distribution with additional location-scale parameters. In addition, and in the light of strongly rejected null hypothesis of normality of forecast errors, I estimate a more flexible parametric form of forecast errors (Pearson family of distributions) and suggest a wider use of this distribution in modeling statistical properties of forecast errors.

IV. Empirical Results

This section addresses the main question of the paper: what is the effect of dissemination standards on the statistical quality of WEO forecasts. To answer the question we perform conditional mean-variance analysis forecast errors. The conditioning variables are area department, subscription/participation in a data dissemination standard and the term of the WEO forecast (Spring or Fall). We also perform conditional covariance analysis to detect possible violations of covariance relationships.

Ideally, we would like to perform an event study that looks purely at the time-series dimension and would compare the behavior of forecast errors along a variety of metrics (bias, efficiency, etc.) for a particular country before the introduction of SDDS or GDDS and after the introduction. This strategy is not feasible for the following two reasons. First, the number of countries, which graduated from GDDS to SDDS, is very small and the time series dimensions are very short as well. Hence, such a study would have very low power. Second, while the subscription to SDDS is marked by a calendar date, the preparation for the subscription can take years. During the preparation period, the quality of country’s data dissemination gradually improves and approaches the SDDS levels. Therefore, we cannot talk about the SDDS graduation/subscription as a discrete event, but rather about the final step in a continuous process.

A. Descriptive Variance Analysis

Table 5 presents mean-variance analysis of the same period real GDP forecast errors. The rows in the table for each department stand for the sample mean, sample standard deviation the value of the t-test for the sample mean and the number of observations respectively. For example, the sample mean of Fall WEO forecasts for GDDS Region 3 countries equals -0.41;

the sample standard deviation for the group equals 1.13 and there are 21 observations in the sample. The same style of presentation is used in other tables in this section.

Table 5 shows that the variance inequality (5) is satisfied for all cases – more information always leads to forecasts with lower variances. In addition, we observe that the sample means of forecast real GDP errors are not statistically different from zero and thus unbiased – the values of t-statistics in never approach any standard critical levels.[8] Since the means of forecast errors in the table are not significantly different from zero in the cross section, it follows that the statistical quality of forecasts can be assessed by studying a single dimension of forecast statistical quality – their variances. If two forecasts are unbiased and have different variances, the lower variance forecast obviously dominates the higher variance forecast.

Table 6 presents mean-variance analysis of the one period ahead real GDP forecast errors. Results show that the variance inequality (5) is satisfied for all cases. The sample means of forecast real GDP errors are not statistically different from zero as indicated by the values of t-statistics.

Table 7 presents the analysis of same period annual inflation rate forecast errors. Results again show that the variance inequality (5) is satisfied for all cases. In addition, we observe that same period annual inflation rate forecasts are unbiased—the values of t-statistics are well below any standard critical value.

Table 8 presents forecast errors for one period ahead annual inflation rate forecasts. The variance inequality (5) is again satisfied in all cases. All forecasts analyzed in the table are unbiased as can be seen from the low values of t-statistics.

B. Variance Equality Tests

The previous section presented an intuitive analysis of differences in variances among SDDS subscribers, GDDS participants and other IMF member countries. In this section, we test the null hypothesis of equal variances across different groups of member countries more formally by using two widely used statistical tests for variance equalities, the Levene test and the Brown-Forsythe test.[9] We do not use the popular Bartlett test because it is very sensitive to departures from normality as was demonstrated by Brown and Forsythe (1974).

Table 9 presents the results of the test for equality of variances for real GDP growth rate forecast errors for the period 1999-2007. The null hypothesis is that the forecasts for SDDS subscribers, GDDS participants and other member countries have equal variances. Both Levene and Brown-Forsythe tests reject the null for the one period ahead forecasts, but not

[8] These results differ significantly from those in Timmernam (2005). The reason for this difference is that Timmernan conducts a time series analysis, whereas the analysis in this paper is based on cross sections. For this reason it is not necessary to deflate the standard deviations by a correction factor $1/\sqrt{N}$.

[9] Both tests are described in the Appendix.

for the same period forecasts. While the forecast variance of in SDDS subscribers is indeed always smaller than in GDDS participants, the difference is only statistically significant for one-year ahead forecasts. This finding supports the intuition that higher frequency and timeliness, required of the countries participating in the IMF data dissemination initiative, results in higher statistical quality of real GDP growth forecasts. This finding is in line with the situation that is graphically presented in Figure 1.

Table 10 presents the results of the test for equality of variances for inflation rate forecast errors for the period 1999-2007. The null hypothesis is that the inflation rate forecasts for SDDS subscribers, GDDS participants and other member countries have equal variances. The null hypothesis is strongly rejected by both the Brown-Forsythe and by the Levene test for the same year forecasts and one-year ahead forecasts. In addition, the variance of the GDDS forecasts is less for same year forecasts and the variance of one-year ahead forecasts is less for SDDS subscribers. This finding is not surprising, since most countries regardless of their participation in the DSI report their inflation data with monthly frequency and with the delay of one month. It implies that we cannot impose an ordering on the quality of inflation forecasts, something we can do for the real GDP growth rate forecast.

A cautionary note is in order—the above results would not have any empirical significance, if the variances of the forecasted variables, that is, the real GDP growth and the CPI inflation rate, differed between SDDS subscribers and GDDS participants. For this reason, we conducted a test of the equality of variances of both ―incoming" variables. We could not reject the zero hypothesis of equal variances, which means that the above results are meaningful.

C. Correlation Analysis

Optimal forecasts should also satisfy the no-correlation condition (6). In addition, due to common aggregate supply and demand shocks that influence both real GDP growth and inflation it is likely that nonzero correlations exist between forecast errors for different macroeconomic aggregates. This section presents results of the conditional correlation analysis for countries that subscribe to SDDS, GDDS participants and all countries combined.

Table 11 presents correlation analysis of the same period real GDP forecast errors. The rows in the table stand for the sample correlation, t-statistic and p-value. For example, the correlation between same period inflation forecast error and one period ahead real GDP forecasts error for SDDS subscribers equals -0.03; the t-statistic is -0.82 and the corresponding p-value is 0.41. Statistically significant correlations are presented in bold. Those statistically significant correlations that violate identity (5) are presented in bold underlined.

There appear to be no significant systematic variations in the correlation structure of the properties of forecasts in
Table 11. In all four cases (SDDS, GDDS, no data dissemination standard and the combined sample), there are three statistically significant correlations that violate identity (5). This

finding suggests that some form of adaptive expectations, is used in forecasting and that data dissemination standards do not play a systematic role here.

V. Conclusion

The paper analyzes the relationship between participation in the IMF's data dissemination standards and the statistical quality of forecasts for the IMF's member countries. The results of the analysis are broadly supportive of the following assertions. First, graduating from GDDS to SDDS broadly improves the statistical quality of forecasts of macroeconomic variables. In the case of the WEO we have found that the variances of real GDP growth rate forecast errors are smaller in SDDS subscribers than in the GDDS participants for one year ahead forecasts, but not for the same year forecasts. Second, the statistical quality of WEO inflation forecasts is significantly better for SDDS subscribers than for the GDDS participants.

Analysis of conditional correlations shows that forecasts of same period and one period ahead real GDP and inflation often violate the no-correlation condition (6) and that there is no systematic variation in these violations between countries with respect to their data dissemination standards.

Parametric estimates of the probability densities of forecast errors show that the forecast errors of real GDP cannot be modeled using standard probability distributions and that normal (Gaussian) distribution is a poor probabilistic model of forecast errors.

The findings in the paper are broadly supportive of the claim that increased SDDS subscription or graduation from GDDS to SDDS will be followed by improvements in the statistical quality of WEO forecasts. In addition, countries participating in neither SDDS nor GDDS have in general less precise WEO forecasts. The practical implications of the study are that the IMF's data standard initiative positively affects WEO forecast statistical quality and by extension improves the necessary conditions to provide member countries with high quality policy advice.

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VII. APPENDIX: THE LEVENE AND BROWN-FORSYTHE TESTS

To test the equality of variances across groups without assuming the normality of underlying distributions we us the Levene and Brown-Forsythe tests. They test the null hypothesis that the population variances are equal in all compared groups.

Both Levene and Brown-Forsythe tests are based on W statistic, which is calculated as follows

$$W = \frac{(N-k)\sum_{i=1}^{k} N_i \left(Z_{i.} - Z_{..}\right)^2}{(k-1)\sum_{i=1}^{k}\sum_{j=1}^{N_i}\left(Z_{ij} - Z_{i.}\right)^2}.$$

In the equation above W is the test statistic, k is the number of different groups to which the samples belong, N is the number of all observations, N_i is the number of observations in group i, and Y_{ij} is the value of the sample observation j from group i.

Z_{ij} is computed differently for the Levene and the Brown-Forsythe test. For the Levene test, one uses $Z_{ij} = \left|Y_{ij} - \overline{Y}_{i.}\right|$ where $\overline{Y}_{i.}$ is the sample mean of group i. For the Brown-Forsythe test $Z_{ij} = \left|Y_{ij} - \overline{Y}_{i.}\right|$ is computed by $\overline{Y}_{i.}$ being the median of group i. The two auxiliary sample means in the expression for the test statistic W are $Z_{..} = \frac{1}{N}\sum_{i=1}^{k}\sum_{j=1}^{N_i} Z_{ij}$ and $Z_{i.} = \frac{1}{N_i}\sum_{j=1}^{N_i} Z_{ij}$.

W is asymptotically distributed as F distribution, with $k - 1$ and $N - k$ degrees of freedom. The Brown-Forsythe test is less sensitive than the Levene test to heavily skewed underlying distributions; the trimmed mean performs best when the underlying distribution is heavy tailed and the median performs best when the underlying distribution is heavily skewed. Using the mean provides the best power for symmetric, moderate-tailed, distributions.

Table 1. Data coverage by years

	Real GDP growth forecast error						Inflation forecast error					
	Same year			One year ahead			Same year			One year ahead		
Year	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
1999	0.33	2.13	170	0.83	2.58	170	-0.41	4.35	168	1.91	8.52	168
2000	0.48	1.87	172	-1.33	2.94	172	0.29	8.40	172	0.78	9.69	172
2001	-0.37	1.89	179	-1.12	2.97	179	-0.40	1.96	180	0.56	4.95	180
2002	0.04	1.76	262	-0.36	2.95	262	0.04	3.38	262	0.50	7.90	262
2003	0.29	1.88	347	0.64	3.25	347	0.23	3.14	347	0.77	5.89	347
2004	0.48	1.61	346	0.38	2.34	346	0.10	3.26	345	1.36	4.33	345
2005	0.39	1.63	350	0.83	3.09	350	0.59	2.20	350	1.35	3.15	350
2006	0.53	1.73	349	0.90	2.68	349	0.36	1.78	349	1.25	3.04	349
2007	0.25	1.43	349	--	--	--	0.24	2.38	349	--	--	--
All	0.30	1.75	2524	0.27	2.96	2175	0.18	3.50	2522	1.07	5.85	2173

Table 2. Data coverage by region

	Real GDP growth forecast error						Inflation forecast error					
	Same year			One year ahead			Same year			One year ahead		
Region (area department)	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
1	-0.11	1.78	543	-0.41	3.18	453	0.42	3.37	543	1.89	6.90	453
2	0.44	1.53	422	0.46	2.66	368	-0.09	3.11	422	0.02	4.46	368
3	0.36	1.44	677	0.29	2.07	596	-0.03	3.67	678	0.63	5.62	597
4	0.66	2.05	419	1.09	3.61	363	0.28	3.35	418	1.52	4.63	362
5	0.24	1.92	463	0.06	3.23	395	0.35	3.85	461	1.36	6.77	393
All	0.30	1.75	2524	0.27	2.96	2175	0.18	3.50	2522	1.07	5.85	2173

Table 3. Descriptive statistics of the forecast errors

	Variable and period			
	GDP_{t+1}	GDP_t	π_{t+1}	π_t
Mean	0.26	0.30	1.07	0.17
Median	0.30	0.10	0.40	0.00
Maximum	27.20	10.20	60.00	60.00
Minimum	-35.30	-9.10	-90.50	-81.00
Std. Dev.	2.96	1.79	5.85	3.65
Skewness	-0.64	0.03	-1.83	-2.14
Kurtosis	21.55	7.42	67.16	160.03
Jarque-Bera statistic	31275.7	1767.6	373723.2	2233172.0
Jarque-Bera p-value	0.0000	0.0000	0.0000	0.0000

Table 4. Parametric estimates of forecast errors for the Pearson family

Variable	Distribution (Pearson type)	b_2	b_1	b_0
GDP_t	Pearson type 4, not related to any standard distribution	0.4466	0.0758	0.1845
GDP_{t+1}	Pearson type 4, not related to any standard distribution	0.1816	-0.3068	0.4553
π_t	Pearson type 1, four-parameter beta	0.5884	-0.7652	-23.676
π_{t+1}	Pearson type 6, F with additional location and scale parameters	0.1883	1.7997	0.4351

Table 5. Mean-Variance analysis of same period annual real GDP forecast errors

Region	Stat.	Spring WEO				Fall WEO			
		SDDS	GDDS	None	All	SDDS	GDDS	None	All
1	Mean	0.16	-0.25	-0.03	-0.21	0.37	-0.04	0.08	-0.01
	Std.	0.94	1.95	2.50	1.99	0.53	1.52	2.18	1.59
	t-value	0.16	-0.13	-0.01	-0.11	0.71	-0.03	0.04	-0.01
	N	9	215	29	253	9	247	34	290
2	Mean	0.79	0.24	0.28	0.49	0.49	0.36	0.28	0.39
	Std.	2.01	1.69	2.00	1.92	0.93	0.94	1.31	1.04
	t-value	0.39	0.14	0.14	0.25	0.53	0.38	0.22	0.38
	N	90	66	49	205	90	72	55	217
3	Mean	0.46	-0.47	-0.05	0.38	0.39	-0.41	0.30	0.34
	Std.	1.78	1.18	0.66	1.74	1.07	1.13	0.60	1.08
	t-value	0.26	-0.40	-0.08	0.22	0.36	-0.36	0.50	0.31
	N	304	21	12	337	305	21	14	340
4	Mean	0.75	0.82	1.00	0.84	0.74	0.47	0.24	0.50
	Std.	2.82	2.18	1.84	2.30	2.26	1.55	1.57	1.76
	t-value	0.27	0.38	0.55	0.36	0.33	0.30	0.16	0.28
	N	54	114	36	204	54	124	37	215
5	Mean	0.13	0.38	-1.18	0.20	0.26	0.30	0.13	0.28
	Std.	2.27	2.29	1.48	2.26	1.35	1.74	0.64	1.54
	t-value	0.06	0.16	-0.80	0.09	0.20	0.17	0.20	0.18
	N	100	111	10	221	102	128	12	242
All	Mean	0.48	0.17	0.27	0.32	0.42	0.18	0.22	0.28
	Std.	2.03	2.06	2.03	2.05	1.26	1.52	1.52	1.42
	t-value	0.24	0.08	0.13	0.16	0.33	0.12	0.14	0.20
	N	557	527	136	1220	560	592	152	1304

Table 6. Mean-Variance analysis of one period ahead annual real GDP forecast errors

Region	Stat.	Spring WEO				Fall WEO			
		SDDS	GDDS	None	All	SDDS	GDDS	None	All
1	Mean	0.12	-0.52	0.47	-0.39	0.11	-0.51	0.03	-0.43
	Std.	1.28	2.81	6.35	3.34	1.21	2.63	5.46	3.04
	t-value	0.10	-0.19	0.07	-0.12	0.09	-0.20	0.01	-0.14
	N	8	177	23	208	8	209	28	245
2	Mean	0.38	0.30	0.98	0.49	0.35	0.33	0.72	0.43
	Std.	2.54	2.21	3.76	2.78	2.29	1.92	3.51	2.54
	t-value	0.15	0.14	0.26	0.18	0.15	0.17	0.20	0.17
	N	80	56	42	178	80	62	48	190
3	Mean	0.37	-0.71	-0.39	0.28	0.40	-0.63	-0.26	0.31
	Std.	2.20	1.34	1.04	2.14	2.06	1.26	0.96	2.01
	t-value	0.17	-0.53	-0.38	0.13	0.19	-0.50	-0.27	0.15
	N	269	18	10	297	270	18	11	299
4	Mean	1.25	0.98	1.37	1.12	1.14	1.03	1.01	1.06
	Std.	3.57	4.74	2.29	4.08	3.36	3.30	2.02	3.12
	t-value	0.35	0.21	0.60	0.28	0.34	0.31	0.50	0.34
	N	48	97	31	176	48	107	32	187
5	Mean	-0.21	0.25	-1.17	-0.02	0.10	0.28	-1.26	0.13
	Std.	3.65	3.03	3.05	3.34	3.44	2.95	1.92	3.14
	t-value	-0.06	0.08	-0.38	-0.01	0.03	0.10	-0.66	0.04
	N	88	91	8	187	90	108	10	208
All	Mean	0.35	0.07	0.71	0.27	0.40	0.09	0.40	0.26
	Std.	2.72	3.32	3.94	3.13	2.54	2.81	3.54	2.79
	t-value	0.13	0.02	0.18	0.09	0.16	0.03	0.11	0.09
	N	493	439	114	1046	496	504	129	1129

Table 7. Mean-Variance analysis of same period annual inflation forecast errors

Region	Stat.	Spring WEO				Fall WEO			
		SDDS	GDDS	None	All	SDDS	GDDS	None	All
1	Mean	-0.23	0.98	0.34	0.86	-0.18	0.07	-0.07	0.04
	Std.	1.57	4.06	3.78	3.97	1.19	2.57	3.68	2.69
	t-value	-0.15	0.24	0.09	0.22	-0.16	0.03	-0.02	0.02
	N	9	215	29	253	9	247	34	290
2	Mean	-0.34	0.28	-0.36	-0.14	-0.19	-0.18	0.38	-0.04
	Std.	1.30	3.44	5.46	3.41	0.58	1.34	5.31	2.80
	t-value	-0.26	0.08	-0.07	-0.04	-0.32	-0.13	0.07	-0.01
	N	90	66	49	205	90	72	55	217
3	Mean	-0.09	-0.71	0.17	-0.12	0.11	-0.61	-0.11	0.05
	Std.	5.24	2.05	0.74	5.00	1.42	1.76	0.89	1.43
	t-value	-0.02	-0.34	0.24	-0.02	0.08	-0.35	-0.13	0.04
	N	304	21	12	337	305	22	14	341
4	Mean	0.22	0.91	-0.46	0.49	-0.02	0.37	-0.72	0.09
	Std.	4.53	3.29	4.84	3.96	1.60	2.52	3.91	2.65
	t-value	0.05	0.28	-0.09	0.12	-0.01	0.15	-0.18	0.03
	N	54	114	35	203	54	124	37	215
5	Mean	0.31	0.74	3.60	0.67	-0.31	0.35	-0.05	0.05
	Std.	6.60	3.28	7.21	5.24	1.34	2.06	1.31	1.78
	t-value	0.05	0.22	0.50	0.13	-0.23	0.17	-0.04	0.03
	N	99	111	10	220	101	128	12	241
All	Mean	-0.03	0.76	0.11	0.32	-0.03	0.14	-0.07	0.04
	Std.	5.00	3.61	4.92	4.45	1.33	2.31	4.13	2.27
	t-value	-0.01	0.21	0.02	0.07	-0.02	0.06	-0.02	0.02
	N	556	527	135	1218	559	593	152	1304

Table 8. Mean-Variance analysis of one period ahead annual inflation forecast errors

Region	Stat.	Spring WEO				Fall WEO			
		SDDS	GDDS	None	All	SDDS	GDDS	None	All
1	Mean	0.11	2.69	1.15	2.42	0.02	1.54	1.14	1.45
	Std.	2.91	5.86	4.00	5.63	2.68	8.23	5.21	7.81
	t-value	0.04	0.46	0.29	0.43	0.01	0.19	0.22	0.19
	N	8	177	23	208	8	209	28	245
2	Mean	-0.16	0.85	-0.80	0.01	-0.15	0.31	-0.02	0.03
	Std.	2.31	3.72	7.28	4.40	1.91	4.06	7.40	4.53
	t-value	-0.07	0.23	-0.11	0.00	-0.08	0.08	0.00	0.01
	N	80	56	42	178	80	62	48	190
3	Mean	0.69	-0.48	0.44	0.61	0.76	-0.64	0.22	0.65
	Std.	6.99	1.84	1.58	6.68	4.52	1.93	1.66	4.34
	t-value	0.10	-0.26	0.28	0.09	0.17	-0.33	0.13	0.15
	N	269	18	10	297	270	19	11	300
4	Mean	0.70	2.57	1.46	1.87	0.08	1.81	0.84	1.20
	Std.	3.54	4.99	5.30	4.74	2.78	4.84	5.25	4.52
	t-value	0.20	0.51	0.28	0.39	0.03	0.37	0.16	0.27
	N	48	97	30	175	48	107	32	187
5	Mean	1.03	1.77	5.07	1.57	0.48	1.42	4.73	1.18
	Std.	6.21	6.71	6.03	6.47	8.79	5.16	6.58	7.04
	t-value	0.17	0.26	0.84	0.24	0.05	0.27	0.72	0.17
	N	87	91	8	186	89	108	10	207
All	Mean	0.60	2.11	0.72	1.25	0.49	1.34	0.84	0.91
	Std.	5.98	5.58	5.89	5.84	5.14	6.40	6.11	5.86
	t-value	0.10	0.38	0.12	0.21	0.09	0.21	0.14	0.15
	N	492	439	113	1044	495	505	129	1129

Table 9: Test for equality of variances, annual real GDP growth rate forecast errors

	Same period			One period ahead		
Test	df	Value	Probability	df	Value	Probability
Levene	(2, 2521)	0.52	0.5940	(2, 2172)	2.78	0.0620
Brown-Forsythe	(2, 2521)	0.32	0.7270	(2, 2172)	2.55	0.0782

By group								
Data standard	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.
SDDS	1117	1.69	1.10	1.09	989	2.63	1.80	1.80
GDDS	1119	1.80	1.16	1.13	943	3.05	1.93	1.93
None	288	1.77	1.14	1.13	243	3.73	2.17	2.16
Entire sample	2524	1.75	1.13	1.11	2175	2.96	1.90	1.90

Table 10: Test for equality of variances, annual inflation rate forecast errors

	Same period			One period ahead		
Test	df	Value	Probability	df	Value	Probability
Levene	(2, 2519)	24.49	0.0000	(2, 2170)	13.76	0.0000
Brown-Forsythe	(2, 2519)	22.03	0.0000	(2, 2170)	12.74	0.0000

Category								
Data standard	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.
SDDS	1115	3.65	1.02	1.02	987	5.57	2.22	2.18
GDDS	1120	3.01	1.82	1.76	944	6.04	3.38	3.30
None	287	4.51	2.12	2.12	242	5.99	3.29	3.28
Entire sample	2522	3.50	1.50	1.47	2173	5.85	2.84	2.79

Table 11. Covariance analysis of real GDP and inflation forecast errors

	All (N=2202)			SDDS (N=989)			GDDS (N=964)			No diss. std. (N=249)		
	GDP_{t+1}	GDP_t	π_{t+1}	GDP_{t+1}	GDP_t	π_{t+1}	GDP_{t+1}	GDP_t	π_{t+1}	GDP_{t+1}	GDP_t	π_{t+1}
GDP_t	**0.22**			**0.49**			**0.42**			**-0.48**		
	10.34			17.48			14.48			-8.53		
	0			0			0			0		
π_{t+1}	-0.02	-0.01		**-0.12**	**-0.11**		-0.02	-0.01		-0.13	0.06	
	-0.93	-0.45		-3.64	-3.35		-0.77	-0.31		-2.1	0.93	
	0.35	0.65		0	0		0.44	0.76		0.04	0.35	
π_t	**0.05**	**-0.07**	**0.09**	-0.03	**-0.11**	**0.69**	**0.11**	**-0.07**	**0.09**	**-0.11**	-0.04	**0.46**
	2.44	-3.12	4.35	-0.82	-3.51	30.24	3.35	-2.2	2.89	-1.72	-0.65	8.17
	0.01	0	0	0.41	0	0	0	0.03	0	0.09	0.52	0

Figure 1: An example of SDDS and GDDS periodicity and timeliness requirements

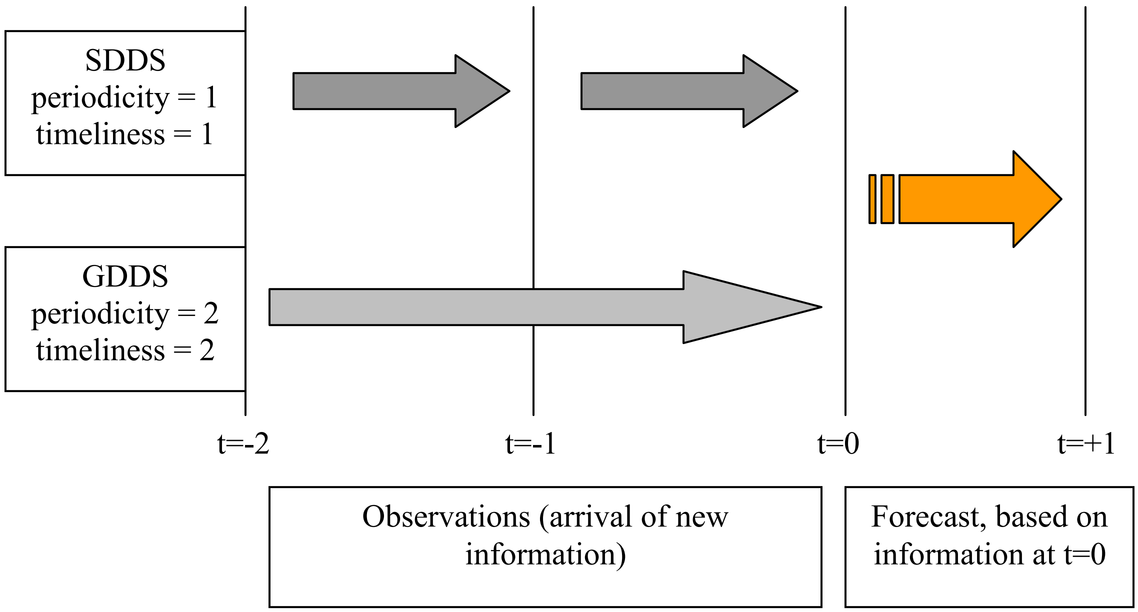

Figure 2. The shape of the same period real GDP forecast error distribution