Do Transparency Standards Improve Macroeconomic Forecasting?

Hui Tong^{*}

Bank of England

January 10, 2005

Abstract

Since the Mexican and Asian crises, there has been a proliferation of international initiatives, including an ambitious standard-setting agenda, to encourage banks, firms and governments to disclose more information about their financial affairs. This paper studies whether and how such transparency standards affect the information efficiency of macroeconomic forecasts. I analyze a panel dataset of quarterly macroeconomic forecasts for sixteen countries during the period 1996-2003. I find that disclosure standards have more positive impacts on the accuracy of IMF forecasts than on that of private forecasts. I further find that IMF forecasts are no longer encompassed by private forecasts after transparency standards' implementation. To explain these findings, I then develop an information model that allows for the correlation between the noisy terms in private and public signals. This model, together with the analyses of institutional features of IMF operation, illustrates how public disclosure could help IMF forecasts add something to the explanatory power of private forecasts.

EFM Classifications: 620,630

^{*} Bank of England, Threadneedle Street, London, EC2R 8AH, UK. Email: hui.tong@bankofengland.co.uk. Tel: +44-207-6015891. Fax: +44-207-6015080. I am particularly grateful to Barry Eichengreen for guidance, encouragement and patience. I would also like to thank Richard Lyons, Daniel McFadden, and Maurice Obstfeld for helpful comments. All remaining errors are mine. This paper represents the views of the author and should not be thought to represent those of the Bank of England.

1. Introduction

The 1990s saw a wave of initiatives, including an ambitious international standard-setting agenda, designed to encourage banks, firms and governments to disclose more information about their financial affairs. This movement gained traction following the 1997 Asian crisis, which many analysts blamed at least partly on the opacity of financial, corporate and government finances in the region (Goldstein 1998). The conclusion drawn by organizations like the International Monetary Fund, the World Bank, and governments like those of the United States and other G-7 members was that greater transparency was a key to reconciling international capital mobility with financial stability.

A range of international initiatives followed. The IMF adopted the Special Data Dissemination Standard (SDDS) for countries active on international financial markets. The IMF and the World Bank established and undertook periodic Reviews of Standards and Codes (ROSCs) to assess the adequacy of their members' compliance with the growing proliferation of international transparency standards. The Financial Stability Forum was created in 1999 at the initiative of G7 group to further promote the promulgation of standards and codes. These organizations all argued that standards would promote international financial stability by facilitating better-informed lending and investment decisions, improving market integrity, and reducing the risks of financial distress.

So far there have been twelve important standards and codes under three categories: financial sector standards, market integrity standards, and transparency standards. Financial sector standards touch banking supervision, securities, and insurance. Market integrity standards

concentrate on auditing and accounting. Transparency standards cover data transparency, fiscal policy transparency and monetary policy transparency.

In this paper, I examine whether data transparency standards have their intended effects in improving information efficiency. I focus on whether and how transparency standards affect macroeconomic forecasting. I distinguish between private forecasts and those of international organizations such as the IMF *World Economic Outlook*. I analyze a panel dataset on GDP growth forecasts for sixteen countries during the period from 1996 to 2003. Transparency standards are found to improve forecasts of private sectors and the IMF with larger impact on the latter.

Forecast encompassing tests further suggest that private forecasts no longer encompass IMF forecasts after standards' implementation. Before the implementation, private forecasts encompassed IMF forecasts, so the latter did not provide additional information that had not been included in the former. However, after the implementation, IMF forecasts started to contain useful information that has not been contained in private forecasts.

To explain these empirical findings, I then propose an information model that considers the correlation between the noisy terms in private and public signals. Although public disclosure could increase the accuracy more for IMF forecasts than for private forecasts, this alone does not necessarily suggest that IMF forecasts will add anything to the explanatory power of private forecasts. However, if standards' implementation provides the IMF with additional private information, or if the noisy term in public information is correlated with that in IMF's private information, then IMF forecasts could contain information that has not been included in private forecasts. The rest of the paper is organized as follows. I begin in this next section, with an overview of data transparency standards, as well as potential correlations between transparency and macroeconomic forecasting. I will distinguish forecasts by private sectors and international organizations. Next, I describe the data and present empirical estimations and findings. I then present an information model to explain empirical findings, and illustrate situations under which IMF forecasts could be useful to private forecasts. Finally, a conclusion is provided.

2. Transparency and Forecasting

2.1. Transparency Standards

The IMF designed data transparency standards. They have two components: the Special Data Dissemination Standard (SDDS) and the General Data Dissemination System (GDDS). The SDDS is designed to guide countries active in international capital markets. The SDDS sets specific standards that must be observed by subscribing countries. SDDS-subscribing countries commit themselves to publish data according to a standard format, and to explain their data dissemination practices. However, the GDDS is open for all countries and much less prescriptive and demanding. Instead, the GDDS provides recommendations for producing statistics, and emphasize the progress over time toward higher quality data.¹ In this paper, the emphasis is on how data transparency affects macroeconomic forecasts. I concentrate on the SDDS because SDDS-subscribing countries must follow disclosure practices required by the IMF, while GDDS-subscribing countries are not required to.

The IMF has encouraged the subscription to the SDDS since April 1996. To date, there have been fifty-seven subscribers. They commit to provide timely information to the IMF in eighteen data categories covering four sectors of the economy: the real sector (such as national

¹ For more information, see http://www.imf.org/external/standards/index.htm.

accounts and forward-looking indicators), the public sector (such as government revenue, spending and debt), the financial sector (such as money supply, domestic credit, and interest rates), and the external sector (such as international reserves and external debt).² The SDDS considers four dimensions of data dissemination: the comprehensiveness of the data (coverage, periodicity, and timeliness), public access to this information, the integrity of the information provided, and data quality.

2.2. How Transparency Affects Forecasting

The SDDS is designed to facilitate timely and accurate data distribution. But does it really help in forecasting macroeconomic indicators? There could be several scenarios:

First, the SDDS might improve forecasting accuracy because it provides additional information to forecasters. For example, subscribing countries provide more frequent updates on government budget deficit so that forecasters can have timely information. Or for example, private forecasters may not have information on a country's foreign debt, such as the amount and maturity breakdown. The public disclosure of the debt structure could in principle facilitate private forecasters to forecast GDP and exchange rate, etc.

Secondly, the SDDS may not have effect on the forecasting. One possibility is that forecasters do not incorporate the information from the SDDS into forecasting. There have been concerns that the private sector is not familiar with the 12 key international standards and codes mentioned earlier, let alone the incentives and abilities to use well the information from

² For more details, see http://dsbb.imf.org/Applications/web/sddshome/.

transparency standards (Clark and Drage, 2000). In this paper, I focus on forecasts given by the Economist Intelligence Unit (EIU), where analysts do refer to the information from the SDDS.³

Finally, the SDDS may decrease forecasting accuracy. One possibility is that the information provided by the SDDS has large noise inside. For example, subscribing countries need to publish quarterly data on GDP in time. Owning to many limitations, published data could be very imprecise, which could hurt forecast accuracy. There has been literature on whether preliminary GDP announcements are really news or just noise. Faust, Rogers and Wright (2003) find that preliminary announcements are just noises sometimes. Another possibility is that the availability of the public signal crowds out the incentive for collecting private information (Tong 2004). Moreover, the crowding-out effect could be large enough to reduce overall forecast accuracy if there is strong herding behavior among private forecasters, where the public signal serves as a focal point. One more possibility, as shown later in this paper, is that if the noisy term in the public information is significantly and positively correlated with the noisy term in IMF's private information, then increased precision of public information could potentially decrease the accuracy of IMF forecasts.

2.3. Two Types of Forecasters

For the forecasting of macroeconomic indicators, we have forecasts from international organizations, such as the IMF's *World Economic Outlook* (WEO), and the OECD's *Economic Outlook*. Since 1984, the biannual WEO has given projections for current-year's GDP, consumer price index and other macroeconomic indicators for all developed countries and most developing countries. The WEO is based on IMF's global assumptions and consultations with member

³ For example, in the August 1999 EIU's country report for India, it said "Quarterly GDP figures, which were recently introduced in order to comply with the special data-dissemination standards introduced by the IMF, show that agricultural output grew by 13.7% year on year in the fourth quarter of 1998/99".

countries. The OECD's *Economic Outlook* is also twice a year, covering its 30 member countries and selected developing countries. The *Economic Outlook* provides prediction for a variety of macroeconomic indicators for up to two years.

In the meantime, we also have forecasts from private sectors, such as the Economist Intelligence Unit (EIU), Consensus Economics, and investment banks. The private sector tends to provide more frequent updates, usually quarterly or even monthly. The EIU studies each country's political, economic and policy trends, and provides country reports with forecasts to its customers. Consensus Economics, on the contrary, does not have its own analyst group. Instead, it surveys a group of outside experts and provides the mean and standard deviation of experts' forecasts.

The participation of international organizations is an important feature of macroeconomic forecasting, because international organizations are absent from the forecasting of microeconomic variables, such as individual firms' profits. Private forecasters may take into account the forecasts of international organizations. For example, EIU forecasts frequently refer to IMF forecasts. One explanation could be that the IMF has closer ties with governments and may have access to some data that are not available to private forecasters. But the IMF may have biased forecasts owing to certain political concerns. For example, the IMF tends to give too optimistic forecasts to countries that are under reforms as required by IMF-supported policy programs (Demasi 1996, and Beach, Schavey, and Isidro, 1999). Moreover, as stated in the WEO, the IMF consults with member countries about its forecasts before publishing the WEO (Batchelor 2000). Private forecasts are likely to recognize IMF's political bias, and differ from the IMF frequently on forecasts.

If a country implements the SDDS and publishes data timely and accurately, then the IMF may get more accurate information from the government. So the IMF may be able to forecast better. With SDDS implementation, macroeconomic data also becomes available to the public. Then private forecasters may be able to forecast more accurately too. More importantly, private forecasters may rely less on the WEO because macroeconomic data that are previously only available to governments and international organizations become available now to the public. However, private forecasters could also rely more on the WEO if IMF forecasts become more accurate after SDDS implementation. So whether private forecasters would rely more on the WEO after SDDS implementation essentially is an empirical question, which this paper will turn to now.

3. Empirical Estimation

3.1. Data

To construct the SDDS implementation index, I rely on the dates when the IMF concludes that a country meets all the requirements of the SDDS. Before that date, the index takes the value of 0. After that date, the index takes the value of $1.^4$ SDDS implementation occurred mainly in 2000 and 2001. So far, there have been 57 countries that meet the requirements, and most countries are developed countries and emerging markets.

Forecasts are from the WEO and EIU country reports. I use the WEO instead of the OECD's *Economic Outlook* in that the former has broad country coverage while the latter focus mainly on OECD's 30 member countries. The WEO is published usually in May and October,

⁴ Or one can focus on the implementation of certain specific SDDS requirements. For example, one can look at the disclosure of quarterly GDP. Some related information is in newspapers and IMF's four reviews of the SDDS. Since the time series is short, information on a large number of countries needs collecting in order to employ a good cross-country analysis.

sometimes in April and September. EIU reports are available quarterly since 1996 for all countries, and monthly since 1998 for major countries. One attractive feature of the EIU report is that it uses the information from the SDDS, as stated in some EIU reports.⁵ Moreover, EIU reports is a very important private forecasting source for developing countries. EIU country reports cover around 200 countries. Each report examines and explains the issues shaping the countries: the political scene, economic policy, domestic economy, foreign trades, etc. Its detailed forecasts complement the analysis and pinpoint political and economic trends. EIU reports have been heavily cited in leading business journals and newspapers. For example, the Oct 31, 2003 issue of the Wall Street Journal (Eastern edition) wrote, "As the Economist Intelligence Unit reported this week, 'The government (Dominica Republic) has raised taxes in order to close the fiscal gap, but it is unclear whether it will have the political will to cut spending. After contracting by 3.2% in 2003, the economy will contract again in 2004, by 0.7%, as inflation erodes real purchasing power, and high interest rates and a loss of confidence curb investment." However, the EIU report series is relatively short (from 1996 till now). And it is impossible to estimate the dispersion of forecasts among EIU analysts, since only a single forecast number is provided in each report.

Among forecasted variables, this paper focuses on the real GDP growth rate because it is a key variable covered in all macroeconomic forecasts.⁶ The actual real GDP growth rate is collected from the World Bank's *World Development Indicators* dataset. Because it is usually difficult to forecast long-term growth, I focus on the projection of current year's growth rate. For example, I look at the projection of year 2001's growth rate as reported in the May 2001 WEO.

⁵ See footnote 3.

⁶ Future work could be extended to consumer price index that also has broad coverage.

3.2. The SDDS and IMF Forecasts

I define the forecast error as the signed difference between actual and forecast:

Forecast
$$Error = Actual_{it} - Forecast_{it}$$
,

and the absolute forecast error as:

Absolute Forecast
$$Error_{it} = |Actual_{it} - Forecast_{it}|$$

for country i and the forecast given at time t. A forecast is said to be more accurate when its absolute forecast error is smaller.

I estimate the following model to examine how the SDDS affects forecast accuracy:

Absolute Forecast Error_{it} =
$$\alpha_0 + \alpha_1 SDDS_{it} + \alpha_2 Timedif_{it} + u_{it}$$

*Timedif*_{*it*} is the variable that measures the time difference from the forecasting month to December. *Timedif*_{*it*} controls for the possibility that forecasts given in May are likely to be less accurate than those given in October. u_{it} is the shock term.

The data sample is from 1996 to 2003, covering all countries that have subscribed to the SDDS in this period. The 1st column of Table 1 reports an OLS regression. The 2nd column adds to the OLS estimation with country dummies, as well as an additional explanatory variable: absolute change in real GDP growth rate. If a forecast model is based on past information, then forecast accuracy could be lower when real GDP changes more dramatically. That is to say, forecast accuracy could be higher simply because of smaller surprise in the forecasted variable. So I add this additional explanatory variable in the 2nd column. The first two columns show that SDDS implementation significantly increases the forecast accuracy of the WEO.

The 3rd column presents the estimation with year dummies and country random effects. The 3rd column suggests the same effect for the SDDS (-0.30), though different from zero only at the seven per cent significance level owning to the relatively large standard error. The 4th column is

similar to the 3rd column but with a much larger sample. All countries in the WEO are examined, including those that have not subscribed to the SDDS. Another difference is that I exclude extreme absolute forecast errors that are bigger than six per cent.⁷ With the doubled sample size in the 4th column, the SDDS is found to have significant negative impact on absolute forecast error. One concern with country random effect is that explanatory variables might be correlated with random effects, which could bias the estimations. So I perform a Hausman type specification test, which essentially compares random effect estimation and fix effect estimation. The null hypothesis of no correlation can not be rejected with the p-value being 0.44. When the assumption of no correlation is satisfied, random effect models tend to give more efficient estimations (i.e. lower standard errors) than fixed effect models. So I present random effect estimation in Table 1.

One might be concerned that the impact of *timedif* on forecast accuracy is nonlinear and that the nonlinearity might effect the estimation for the SDDS. So based on the 4th column, I add explanatory variables related to the nonlinearity of *timedif*: the square of *timedif*, the square root of *timedif*, or the log of *timedif*. The nonlinearity turns out to be insignificant, and the estimated coefficient for the SDDS remains essentially unchanged.

One might also be concerned that forecast errors within a given country-year pair might be correlated. For example, both April and September 2002 WEO gave forecasts for Mexico's growth rate. Then the forecast error for April and September are likely to be correlated because they both are affected by Mexico's actual growth rate in 2002. To control for this correlation within each country-year pair, I estimate a random country-year pair effect model, where observable explanatory variables are SDDS implementation, *Timedif*, actual change in growth rate, country dummies, and year dummies. The sample selection is the same as the 4th column

⁷ The exclusion alone decreases the sample size by four per cent.

and gives us 1273 observations. Because the WEO is published twice a year, we have 653 country-year pairs on which the random effect applies. The result is in the 5th column. Again, SDDS implementation increases forecast accuracy significantly. I also run Hausman specification test to see whether explanatory variables are correlated with random effects. The null hypothesis of no correlation can not be rejected with the p-value being 0.54.

This result may seem surprising in that the SDDS was designed to enhance the provision of information by governments to the public (to the markets), in order to strengthen market discipline and cause fewer unpleasant shocks that might destabilize the market. Since the IMF management and staff is able to collect inside governmental information through confidential Article IV consultations with member countries, the public disclosure of governmental data would not necessarily enhance the IMF's own forecasts. So it may not be very intuitive that SDDS subscription in fact increases IMF forecast accuracy as well.

One explanation could be that when a country meets the requirements of the SDDS, it also is forced to provide more accurate and/or more timely data to the IMF itself, with the result that WEO forecasts become more accurate. Under Article IV of the IMF's Articles of Agreement, the IMF holds bilateral discussions with members. Every year, a staff team visits a country, collects economic and financial information, and discusses with officials the country's economic developments and policies. After the visit, a report is prepared to form the basis for discussion by the IMF's Executive Board. However, the consultation is usually once per year. For example, the IMF visited Tunisia for only two weeks from May 6-19 for year 2003's Article IV consultations.⁸ But the two issues of WEO for 2003 were published in April and September 2003 respectively. Then the quarterly disclosure of Tunisia's macroeconomic indicators through the SDDS could provide timely information for the WEO preparation.

⁸ http://www.imf.org/external/country/TUN/

There is another possibility. WEO forecasts might be biased by "political considerations," especially in the cases of countries that have programs with the Fund (programs in whose success the Fund feels that it has a vested interest). It is possible that the disclosure of more information through the SDDS makes it more difficult for the IMF to issue forecasts that it knows are biased (but that it nonetheless would prefer to issue for the aforementioned political reasons) because these are now blatantly inconsistent with the country's own public data releases. To test this hypothesis, I added two additional explanatory variables to the 5th column: the IMF program dummy and the IMF dummy interacted with SDDS implementation. To construct the program dummy, I collect the total agreed amount of Stand-by Arrangements and the Extended Fund Facility (EFF) from IMF's International Financial Statistics dataset, and record the program dummy as one for each country-year when the amount is not zero.⁹ The results are in the sixth column of Table 1. One can see that even with the inclusion of IMF programs, SDDS implementation still have positive impact on forecast accuracy at six per cent significance level. One can also see that the IMF program dummy decreases forecast accuracy, and its effect does not change dramatically after SDDS implementation.

3.3. The SDDS and EIU forecasts

This subsection examines how the SDDS affects EIU forecasts. The sample covers 15 countries and Hong Kong SAR from 1996 to 2003.¹⁰ These areas have implemented the SDDS over time so we can perform the before-and-after analysis. In this sample, EIU forecasts are quarterly. For example, for Argentina, EIU forecasts in February, June, September and December were used for the year 1998. The dependent variable is the absolute forecast errors of

⁹ For more details on IMF lending, see http://www.imf.org/external/np/exr/facts/howlend.htm.

¹⁰ These 15countries are: Argentina, Brazil, Chile, Colombia, Hungary, Indonesia, Korea, Malaysia, Mexico, Peru, Philippines, Poland, Singapore, Thailand, and Turkey.

EIU forecasts, and the explanatory variables are the SDDS implementation dummy and the time difference from the publication of EIU reports to December. Column 1 of Table 2 reports standard OLS regression, column 2 reports the estimation with country fixed-effect, and column 3 presents the estimation with both country fixed effects and year dummies. The first two columns suggest that SDDS implementation significantly increases the forecast accuracy of EIU reports. The SDDS has the same sign in column 3, though not significant because the estimated standard error is relatively large. Column 4 estimates the same model as in column 2 with one additional independent variable: absolute change of real GDP growth rate. SDDS implementation turns out to have significant effect. The result on the EIU is intuitive in that countries subscribing to the SDDS are required to disclose to the public the information on macroeconomic indicators accurately and timely, which could help the private sector with its forecast.

Here, I also consider the potential nonlinearity of *timedif*'s impact on forecast accuracy. Based on the 4th column, I add independent variables that controls for the nonlinearity of *timedif*: the square of *timedif*, the square root of *timedif*, or the log of *timedif*. The nonlinearity does not turn out to be significant, and the estimated coefficient for the SDDS remains almost unchanged.

3.4. EIU v.s. IMF Forecasts

I further study whether the SDDS affects EIU reports and the WEO differently. Because EIU country reports frequently refer to the WEO, EIU forecasts may have imbedded the information contained in the WEO. Then it will not be a surprise if EIU forecasts are more accurate than the WEO. To control for this effect, I use the EIU forecasts that are one or two months ahead of the WEO. Since the WEO usually comes out in May and October, and April and September sometimes, the EIU forecasts employed will then be those in February, March, April, July, August and September. When EIU reports and the WEO are published in the same month, the EIU forecasts will be included in the estimation, as long as the EIU reports are published ahead of the WEO.

Based on the above sample, I reexamine separately the effects of the SDDS on the WEO and EIU reports. Table 3 shows that the SDDS has larger impact on the WEO than on EIU reports. The impact of the SDDS on the EIU absolute forecast error is -0.56 (1st column), while its impact on the WEO is higher at -0.71. During the sample period of 1996 to 2003, there were some crisis periods, which decreased forecast accuracy significantly. I then exclude absolute forecast errors that are bigger than four per cent. This shrinks the sample size by about nine per cent. The new results are shown in the 3rd and 4th columns of Table 3. Again, the SDDS has higher impact on the WEO than on EIU reports. The impact on the WEO is -0.37, while the impact on EIU reports is only -0.16 and not significantly different from zero.

Table 4 presents the forecast accuracy of EIU reports and the WEO. Before SDDS implementation, the average absolute forecast error across 16 countries and areas is 1.31 and 1.50 for EIU reports and the WEO respectively. So the WEO was especially inefficient, which is consistent with Juhn and Loungani (2002).¹¹ After SDDS implementation, the average decreases to 1.10 and 1.07 for EIU reports and the WEO respectively. So before the SDDS, there is some gap between EIU reports and the WEO, but SDDS implementation eliminates and if anything reverses the gap.

¹¹ They compare the WEO and Consensus Economics for the sample period 1989 to 1999, and find that the WEO is less accurate than Consensus Economics.

3.5. Forecast Encompassing

This subsection studies whether the WEO contain information not already included in EIU reports. To analyze this, I use forecast encompassing tests as in Fair and Shiller (1990), and Holden and Thompson (1997). I look at whether the difference between WEO and EIU forecasts can help explain partially the forecast error of the EIU. That is equivalent to study whether a linear combination of WEO and EIU forecasts gives more accurate forecasts than EIU forecast alone. Note that the superiority of one source of forecasts in terms of forecast accuracy does not necessarily imply that forecasts from other sources contain no additional information.

Suppose two forecasts are f_1 and f_2 . A linear combination of f_1 and f_2 is

$$(1-\beta_1)f_1+\beta_1f_2,$$

where $0 < \beta_1 < 1$. Denote $\overline{\beta_1}$ as the solution to

$$Min_{\beta}(\theta - (1 - \beta_1)f_1 - \beta_1f_2)^2$$
,

where θ is the true value of the forecasted variable. Then a test of f_1 encompassing f_2 is equivalent to testing $\overline{\beta_1} = 0$. If $\overline{\beta_1} = 0$, then f_2 does not add anything to the explanatory power of f_1 . As the estimated $\overline{\beta_1}$ becomes larger, f_2 is more useful to f_1 .

To test the null hypothesis that $\overline{\beta}_1 = 0$, the following econometric model will be estimated:

$$(Actual_{it} - f_{eiu,it}) = \beta_0 + \beta_1(-f_{eiu,it} + f_{weo,it}) + \mathcal{E}_{it},$$

where ε_{it} is a standard disturbance term. If the estimated $\hat{\beta}_1$ is not significantly different from 0, then the above null hypothesis cannot be rejected. A constant term, β_0 , is included to control for the potential bias of EIU forecasts.

The sample includes the WEO and the EIU forecasts that are one or two months ahead of the WEO. The reason for this sample selection is similar to that in the Subsection 3.3: the EIU forecasts published after the WEO may have imbedded the information from the WEO, and then it is difficult to test whether the WEO is useful to EIU reports. Table 5 presents the encompassing test. Before SDDS implementation, $\hat{\beta}_1$ is 0.08, not significantly different from zero (column 1). However, after SDDS implementation, $\hat{\beta}_1$ becomes 0.45, significantly different from zero at the 5% level (column 2). So after SDDS implementation, the WEO is no longer encompassed by EIU reports.

Column 1 and 2 estimate the models separately for before and after SDDS implementation. In column 3, I pool the before and the after together, and estimate the following model:

$$(Actual_{it} - f_{eiu,it}) = \beta_0 + \beta_2 SDDS + (\beta_1 + \beta_3 SDDS)(-f_{eiu,it} + f_{weo,it}) + \varepsilon_{it}$$

 $\hat{\beta}_3$, the impact of the SDDS on forecast encompassing, is large in value (0.36), but not significantly different from zero. Probing deeper, forecast accuracy tend to be smaller during financial crises. I then exclude extreme values owning to crises, and focus on the situations when the absolute forecast error is less than four per cent.¹² $\hat{\beta}_3$ now becomes 0.45, significantly different from zero at the 5 per cent level (column 4). So with the implementation of the SDDS, the WEO is able to provide more information to EIU reports, but not during crisis periods.

I find that both the IMF and the EIU missed financial crises and later-on economic recovery. For example, both the WEO and EIU reports missed not only the 1998 financial crises in Hong Kong, Korea, Malaysia and Thailand, but also the recovery in the second year. Even after SDDS implementation, their ability of forecasting crises does not improve significantly. For example, Argentina had a financial crisis in 2001. The May 2001 WEO forecast for Argentina Real GDP growth rate was two per cent, and the April EIU forecast was 1.9 per cent. Both significantly missed the coming crisis that caused the actual growth rate drop to be –4.4 per cent.

¹² Recall that this shrinks the sample size by nine per cent.

So transparency does not necessarily provide better early warning of crises. Similarly, Argentina had a recovery in 2003 with growth rate being 8.7 per cent. But in April 2003, both the EIU and the IMF forecasted the growth rate being only three per cent. One possible explanation is that their models for forecasting are linear, not suitable for forecasting extreme events such as crises. Moreover, the current literature on crises, such as Obstfeld (1994), regards crises as a result of multiple equilibria, which highlights the difficulty of forecasting crises.

I then look at the question the other way around, and examine whether the WEO encompasses EIU forecasts. For this purpose, I use the EIU forecasts on the same month and one-month after the WEO publication.¹³ The selected EIU reports thus will mainly be those published in May, June, October and November. I focus on the situations when the absolute forecast error is less than four per cent. The following econometric model is estimated:

$$(Actual_{it} - f_{weo,it}) = \beta_0 + \beta_1(-f_{weo,it} + f_{eiu,it}) + \varepsilon_{it}$$

The estimated $\hat{\beta}_1$ is significantly different from zero both before and after SDDS implementation (column 1 and 2 of Table 6), so we reject the null hypothesis that the WEO encompasses EIU forecasts. That is to say, EIU forecasts indeed can provide additional information not contained in the WEO.

This result is consistent with Juhn and Loungani (2002), who find that the WEO does not encompass *Consensus Economics*. One explanation could be that EIU reports are published onemonth later than the WEO, thus EIU reports have additional information for that month that is not inside the WEO. To check it, I further restrict the sample to where the WEO and EIU reports are published in the same month. Again, I find that the WEO does not encompass EIU reports

¹³ Here I allow for same month sample because the WEO publication usually has one-month or two-month lags (Batchelor 2000).

(column 3 and 4 of Table 6).¹⁴ This suggests that private forecasts can provide valuable information to international organizations.

4. Theoretical Model

In the above empirical estimations, there are two main findings:

- The SDDS increases the accuracy of the WEO more than that of EIU reports.
- Since SDDS implementation, combining the WEO and EIU reports will do significantly better in forecasting than EIU reports alone.

I now develop an information model to reconcile these two findings. Note that the first finding does not necessarily imply the second finding. It could well be the case that the WEO has higher forecast accuracy but still contains no information that is not already inside EIU reports. Moreover, both the EIU and the IMF have the same access to data disclosed by the SDDS, which could make the second finding less likely to hold. However, I will show that if the noisy term in public information from the SDDS is correlated with that in IMF's private information, then the WEO could potentially provide more information not already in EIU reports. A contribution of the model here is that it provides a theoretical explanation for the encompassing test, which has so far been largely presented as pure econometric analyses. Furthermore, the model is the first one to explicitly analyze how the correlation between public and private information affects the overall forecast accuracy.

¹⁴ Note that in column 4, $\hat{\beta}_1$ is different from zero only at ten per cent significance level owing to relatively small sample size. Still, $\hat{\beta}_1$ is quite large at 0.69.

4.1. Basic Model

Suppose there are two agents, i = 1, 2. Agent *i* receives both public information,

$$x = \theta + \eta \,, \tag{1}$$

and private information,

$$y_i = \theta + u_i \,. \tag{2}$$

 η is a normally distributed disturbance term, independent of the true fundamental value θ , with mean zero and precision α ($\alpha = \frac{1}{Var[\eta]}$). u_i is also normally distributed, independent of θ and

 η , with mean zero and precision γ_i ($\gamma_i = \frac{1}{Var[u_i]}$). Moreover, u_1 and u_2 are independent. α and

 γ_i are known to agent *i*. I assume further that agent *i* only observe x and y_i , but not y_j .

Based on x and y_i , agent *i* will form his or her forecast of θ according to the following Bayesian updating rule as in Lyons (2001)¹⁵:

$$f_i = \frac{\alpha x + \gamma_i y_i}{\alpha + \gamma_i}.$$
(3)

The variance of the forecast f_i is

$$\operatorname{var}[f_i] = \frac{1}{\alpha + \gamma_i} \ . \tag{4}$$

Given the precision of private information (γ_i) , the marginal effect of public information precision (α) on $\operatorname{var}[f_i]$ is $-\frac{1}{(\alpha + \gamma_i)^2}$.

The SDDS is assumed to affect only public information through simultaneous and free disclosure of information to the public. The above formula for the marginal effect is consistent

¹⁵ See page 108 of Lyons (2001).

with empirical results in Section 3: EIU reports have smaller variance than WEO forecasts before SDDS implementation, and the SDDS has larger impact on the variance of WEO forecasts than on that of EIU reports. Because the WEO has larger variance, i.e.,

$$\frac{1}{\alpha+\gamma_{eiu}} < \frac{1}{\alpha+\gamma_{weo}},$$

the marginal effect on the WEO will be bigger, i.e.,

$$\left(\frac{1}{\alpha+\gamma_{eiu}}\right)^2 < \left(\frac{1}{\alpha+\gamma_{weo}}\right)^2.$$

Recall the econometric model for the forecast encompassing test in Section 3 is:

$$(Actual_{it} - f_{eiu,it}) = \beta_0 + \beta_1(-f_{eiu,it} + f_{weo,it}) + \varepsilon_{it}, \qquad (5)$$

then in population,

$$\beta_{1} = \frac{E[(\theta - f_{eiu,it})(-f_{eiu,it} + f_{weo,it})]}{Var[-f_{eiu,it} + f_{weo,it}]}.$$
(6)

Plugging the formula for f_i (equation 3) into the formula for β_1 , one gets

$$\beta_1 = \frac{\gamma_{weo}}{\gamma_{eiu} + \gamma_{weo}} \,. \tag{7}$$

The precision of public information, α , is absent from equation (7). An intuitive explanation is that both agents receive the same public information, so the public information imbedded in one agent's forecast does not give the other agent any extra information. So if the WEO and EIU reports use exactly the same public information, then more accurate public information, owning to SDDS implementation, will make both the WEO and EIU reports more accurate. But it will not make the WEO contain more information not already in EIU reports.

However, empirical estimations in Section 3 do suggest that after SDDS implementation the WEO contains more additional information not included in EIU reports. To understand this result, some assumptions in the above basic model have to be relaxed.

4.2. Extension One

One possibility is that there is some information available to the IMF that results from SDDS implementation but not disclosed to the public. In this situation, SDDS implementation increases not only α but also γ_{weo} , while having no impact on γ_{eiu} . Then equation (7) suggests that β_1 will be higher. Below I will show that although both the IMF and the private sector have access to the same macroeconomic data disclosed by the SDDS, the IMF has more access to the data-generating process than the private sector does. And this could give the IMF an edge.

During SDDS implementation, the IMF assesses data collecting and reporting and provides technical assistance to subscribing countries. For example, the IMF assessed the Turkish Statistical System and Turkey's integration into the SDDS in 2001. The IMF then provided consultancy services to Turkey on national accounts and price statistics.¹⁶ Similarly, the IMF provided technical helps during Thailand's preparation for the Quarterly Gross Domestic Product (QGDP), whose disclosure is required by the SDDS. There was a technical issue of making quarterly data and preliminary QGDP estimates consistent with the corresponding annual GDP. There are several benchmarking techniques for solving it: the Ginsburg/Nasse method, the Bassie method presented by OECD, and the Denton's least square method recommended by the IMF. In the end, Thailand decided to choose the Denton's method.¹⁷ However, on the Dissemination Standards Bulletin Board for Thailand, which is the main website for SDDS

¹⁶ http://www.die.gov.tr/uid/imf-page-english.htm

¹⁷ http://www.unescap.org/stat/meet/qgdp/qgdp-thailand01.pdf

disclosure, it only states "the revision of quarterly figures is calculated by using mathematical technique so that the sum of four quarters must be equal to the annual estimate", without referring specifically to the Denton's technique.¹⁸

So the IMF could have more influence and knowledge on the data-generating process than the private sector, even though the data per se is disclosed to the public through the SDDS.¹⁹ Thus the IMF may be able to use the data more efficiently than private forecasters.

4.3 Extension Two

Another possible extension is to introduce correlation between disturbance terms η in public information and u_{weo} in IMF's private information. This is a reasonable extension, especially for the WEO. For example, both the public information disclosed through the SDDS and the private information collected by the IMF from confidential Article IV consultations could be based on the same internal governmental reporting system. If there are errors in the internal reporting system, then the correlation between η and u_{weo} could be positive.

I add the correlation between η and u_{weo} into the basic model, and assume the correlation coefficient to be ρ . Thus given θ , public information x and private information y_{weo} could be correlated. I further assume there is no correlation between η and u_{eiu} . Under these assumptions, the joint probability density function of x and y_{weo} is:

¹⁸ http://dsbb.imf.org/Applications/web/sddsctycatbaselist/?strcode=THA&strcat=NAG00

¹⁹ Note that there are other possibilities. For example, there may be information in the timing of data submission to the IMF, or additional information about the integrity of a given month's statistics.

$$f(x, y_{weo}) = \frac{1}{2\pi\sigma_{\eta}\sigma_{u_{weo}}\sqrt{1-\rho^{2}}} \times \exp\left\{\frac{1}{-2(1-\rho^{2})}\left[\left(\frac{x-\theta}{\sigma_{\eta}}\right)^{2} - 2\rho\left(\frac{x-\theta}{\sigma_{\eta}}\right)\left(\frac{y_{weo}-\theta}{\sigma_{u_{weo}}}\right) + \left(\frac{y_{weo}-\theta}{\sigma_{u_{weo}}}\right)^{2}\right]\right\},$$
(8)

where σ_{η} and $\sigma_{u_{weo}}$ are the standard errors of η and u_{weo} respectively. One can take the derivate of the log of $f(x, y_{weo})$ with respect to θ , and calculate the maximum likelihood estimator for θ , $\hat{\theta}$, by setting the derivative equal to zero. The forecast of the WEO, f_{weo} , is always equal to $\hat{\theta}$, which has the following form:

$$f_{weo} \equiv \hat{\theta} = \frac{(\alpha - \rho(\alpha \gamma_{weo})^{0.5})x + (\gamma_{weo} - \rho(\alpha \gamma_{weo})^{0.5})y_{weo}}{\alpha + \gamma_{weo} - 2\rho(\alpha \gamma_{weo})^{0.5}}.$$
(9)

The forecast of the EIU, f_{eiu} , is still the same as the one in the basic model:

$$f_{eiu} = \frac{\alpha x + \gamma_{eiu} y_{eiu}}{\alpha + \gamma_{eiu}}.$$
 (10)

From equation (9), one can show that the variance of f_{weo} is:

$$Var[f_{weo}] = \frac{1 - \rho^2}{\alpha + \gamma_{weo} - 2\rho(\alpha\gamma_{weo})^{0.5}}.$$
(11)

The sign of the derivative $\frac{\partial \operatorname{var}[f_{weo}]}{\partial \alpha}$ depends on the sign of $(\rho \gamma_{weo}^{0.5} - \alpha^{0.5})$. If the

correlation ρ is negative, then $(\rho \gamma_{weo}^{0.5} - \alpha^{0.5})$ is negative and $\frac{\partial \operatorname{var}[f_{weo}]}{\partial \alpha} < 0$, which means

higher precision of public information will increase IMF's forecast accuracy.

However, when ρ is positive, it is more complicated. If $\rho \gamma_{weo}^{0.5} < \alpha^{0.5}$ (i.e., private information is relatively imprecise), then $\frac{\partial \operatorname{var}[f_{weo}]}{\partial \alpha} < 0$, thus more public disclosure will

decrease the absolute forecast error of the WEO. But if $\rho \gamma_{weo}^{0.5} > \alpha^{0.5}$ (i.e., private information is already relatively accurate), then $\frac{\partial \operatorname{var}[f_{weo}]}{\partial \alpha} > 0$, which suggests that more public disclosure could indeed *increase* the absolute forecast error of the WEO. So when IMF's private information is already precise, additional public disclosure through the SDDS could have the unintended effect and decrease IMF's forecast accuracy.

To the author's knowledge, this paper is one of the first to analyze how higher precision of a signal could potentially bring negative overall impact on information efficiency when multiple signals exist and are correlated.²⁰ So a couple of points are worth mentioning:

First, two signals together always provide better or equal inference, compared with one signal alone. $Var[f_{weo}]$ in equation (11) is never larger than $\frac{1}{\alpha}$ (the variance of the WEO when only public information x is available) or $\frac{1}{\gamma_{weo}}$ (the variance of the WEO when only private information y_{weo} is available).²¹ So the WEO will always use both public and private information. However, the weights on realized public and private signals depend on the two signals' relative precision as shown in equation (9).

Secondly, signal x plays two roles: one is to give forecasters direct inference on the fundamental value θ ; the other is to provide forecasters indirect inference on θ by indicating how close to θ the realized y_{weo} is. The latter is owing to the correlation between η and u_{weo} . If

²⁰ Morris and Shin (2004) look at correlated private signals among players in a global game setting where players have incentives to herd. They conclude that players' equilibrium behavior will not be significantly altered by the correlation. Here, I focus more on the correlation between public and private signals available to a single player and how this may affect that player's information efficiency. I suspect that if Morris and Shin (2004) introduce the correlation of public and private signals, then the rationale illustrated here would still apply. Thus here I introduce a complementary mechanism through which higher precision of public information could have negative impact on the social welfare as defined in Morris and Shin (2004), without referring to players' herding incentives.

²¹ Intuitively, one could always discard one of the two signals and go back to the situation where only one signal is available.

forecasters rely more on x's first role, then a positive weight will put on x in equation (9). In the case where $Var[\eta]$ is extremely small, forecasters could just set the forecast equal to x. However, if forecasters rely more on x's second role, then a negative weight might be put on x in cases where ρ is positive.²² When $\rho \gamma_{weo}^{0.5} > \alpha^{0.5}$, the weight on x in equation (9) is negative, which suggests that x's second role is the dominant one.

As x becomes more precise (i.e., $Var[\eta]$ becomes smaller), x could provide forecasters more accurate direct inference on θ , because x is fluctuating in a smaller band around θ . However, at the same time, η becomes less capable of inferring u_{weo} , in that η has less variation than before. That is to say, x is less capable of telling how close to θ the realized y_{weo} is. This bears some analogy to traditional econometrical inference, where smaller variations in explanatory variables tend to cause higher standard errors for estimated coefficients. The overall effect of the higher precision of x then depends on which one of the two effects dominates.

When $\rho \gamma_{weo}^{0.5} > \alpha^{0.5}$, as shown earlier, x's second role is more important to forecasters. In this case, because the higher precision of x benefits x's first role and hurts its second role, the overall effect of more precise x turns out to be negative (i.e., higher $Var[f_{wea}]$).

From equations (6), (9) and (10), one can further derive β_1 , the forecast encompassing coefficient, as:

$$\beta_{1} = \frac{\gamma_{weo} - 2\rho\sqrt{\alpha\gamma_{weo}} + \rho^{2}\alpha}{\gamma_{eiu} + \gamma_{weo} - \rho^{2}\gamma_{eiu} - 2\rho\sqrt{\alpha\gamma_{weo}} + \rho^{2}\alpha} .$$
(12)

²² Positive ρ means that disturbance terms η and u_{weo} tend to move in the same direction. Then subtracting u_{weo} from y_{weo} could be partially done by subtracting a multiplier of η from y_{weo} , which is equivalent to subtracting a multiplier of x from y_{weo} .

If the correlation coefficient ρ is zero, then we are back to equation (7) where the accuracy of public information does not affect forecast encompassing at all. However, if ρ is different from zero, then public information could affect forecast encompassing.

From equation (12), one can derive the derivative $\frac{\partial \beta}{\partial \alpha}$, whose sign depends on $(\rho \alpha^{0.5} - \gamma_{weo}^{0.5})$. If $\rho \alpha^{0.5} > \gamma_{weo}^{0.5}$ (i.e., private information is relatively imprecise), then $\frac{\partial \beta}{\partial \alpha} > 0$, and higher precision of public information from the SDDS will cause the WEO provide additional information to the EIU.²³ Thus, when $\rho \alpha^{0.5} > \gamma_{weo}^{0.5}$, we have theoretical results that are consistent with the empirical results in Section 3.

One can also think of other possible theoretical extensions that could support empirical findings in Section 3. However, these extensions should be based on the real operating procedure of the SDDS or the forecast-generating processes of the WEO and EIU reports as shown in the above two extensions. As a future work, it will also be interesting to see which one of the two extensions fits the real situation better. That is to say, whether it is the additional private information or the correlation between public and private information that gives the IMF an edge.

5. Conclusion

This paper studies how data transparency standards affect macroeconomic forecasts. I find that the SDDS improves both the forecast accuracy of the WEO and EIU reports, with larger

²³ Note that $\rho \alpha^{0.5} > \gamma_{weo}^{0.5}$ also implies $\alpha^{0.5} > \rho \gamma_{weo}^{0.5}$, because the correlation coefficient ρ is between –1 and 1. When $\alpha^{0.5} > \rho \gamma_{weo}^{0.5}$, as shown earlier, more accurate public information increases the forecast accuracy of the WEO.

impact on the former. By applying encompassing tests, I further find that the WEO becomes more informative to EIU reports after SDDS implementation. I then propose an information model with correlated public and private signals to illustrate circumstances under which the WEO could be more informative to EIU reports. If the process of SDDS implementation provides the IMF with additional private information, or if the noisy term in public information disclosed by the SDDS is correlated with that in IMF's private information, then the SDDS could cause the WEO to provide more information that has not been included in EIU reports.

	OLS	OLS	Random	Random	Random	IMF
	(SDDS	(SDDS	Country	Country	Country-Year	Programs
	Countries)	Countries)	Effects	Effects	Pair Effects	(All
			(SDDS	(All	(All	Countries)
			Countries)	Countries)	countries)	
α_1 (SDDS)	-0.42	-0.47	-0.30	-0.28	-0.25	-0.24
α_1 (5005)	(0.10)	(0.08)	(0.17)	(0.10)	(0.12)	(0.13)
α_2 (Timedif)	0.11	0.11	0.11	0.07	0.07	0.07
α_2 (<i>Timedif</i>)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Absolute		0.22	0.26	0.17	0.16	0.16
change in GDP growth rate		(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
IMF program						0.33
						(0.17)
IMF program						-0.13
interacted with SDDS						(0.23)
Year 1997			0.32	0.33	0.38	0.34
			(0.23)	(0.13)	(0.17)	(0.17)
Year 1998			0.13	0.10	0.15	0.15
			(0.23)	(0.13)	(0.17)	(0.17)
Year 1999			0.31	0.28	0.31	0.29
			(0.22)	(0.13)	(0.17)	(0.17)
Year 2000			0.13	0.28	0.31	0.28
			(0.19)	(0.12)	(0.16)	(0.16)
Year 2001			0.16	0.13	0.13	0.17
			(0.17)	(0.11)	(0.15)	(0.15)
Year 2002			0.01	0.12	0.06	0.05
			(0.16)	(0.11)	(0.14)	(0.14)
Year 2003						
Constant	0.87	0.48	0.16	0.61	-0.43	1.57
	(0.11)	(0.1)	(0.24)	(0.13)	(1.01)	(1.00)
No. of observation	785	685	685	1273	1273	1249
R-squared	0.06	0.40	0.41	0.25	0.52	0.52

Table 1. The Impact of the SDDS on the WEO

Note: Standard errors are in parentheses. Coefficients different from zero at 5% level are in bold.

	OLS	Country Fixed Effects	Country Fixed Effects	Country Fixed Effects
α_1 (SDDS)	-0.57 (0.15)	-0.64 (0.14)	-0.28 (0.28)	-0.44 (0.13)
α_2 (Timedif)	0.18 (0.02)	0.17 (0.02)	0.18 (0.02)	0.18 (0.02)
Absolute change in GDP growth rate				0.21 (0.02)
Year 1997			0.23 (0.24)	
Year 1998			1.00 (0.25)	
Year 1999			1.22 (0.25)	
Year 2000			0.15 (0.28)	
Year 2001			0.53 (0.33)	
Year 2002			0.07 (0.36)	
Year 2003			-0.03 (0.39)	
Constant	0.81 (0.15)	0.78 (0.35)	1.27 (0.39)	0.04 (0.32)
No. of observation	533	533	533	464
R-squared	0.15	0.3	0.35	0.50

Note: Standard errors are in parentheses. Coefficients different from zero at 5% level are in bold.

	EIU	IMF	EIU	IMF
	Forecast	Forecast	Forecast	Forecast
α_1 (SDDS)	-0.56	-0.71	-0.16	-0.37
	(0.21)	(0.23)	(0.14)	(0.17)
α_2 (timedif)	0.17	0.17	0.08	0.09
	(0.04)	(0.05)	(0.03)	(0.03)
No. of observation	193	193	176	176
R-squared	0.31	0.30	0.28	0.25

 Table 3. Comparing SDDS's Impact on EIU and IMF Forecasts

Note: Standard errors are in parentheses. Coefficients different from zero at 5% level are in bold. Estimations cover 16 countries with country fixed-effect included. Columns 1 and 2 include extreme values. Columns 3 and 4 exclude extreme values.

Table 4. EIU vs. WEO Forecasts				
	EIU absolute forecast error (Mean)	WEO absolute forecast error (Mean)		
Before the SDDS	1.31	1.50		
After the SDDS	1.10	1.07		
Note: Extreme forecast	errors (lager than 4% in absolu	ite sense) are excluded.		

	Before SDDS	After SDDS	Pooled Estimation	No extreme value
β_0	37	0.15	-0.37	27
10	(0.24)	(0.19)	(0.21)	(0.15)
β_1	0.08	0.45	0.08	0.02
/ 1	(0.22)	(0.22)	(0.20)	(0.15)
β_2			0.51	0.37
<i>I</i> = 2			(0.31)	(0.22)
β_3			0.36	0.45
1-3			(0.33)	(0.23)
No. of	110	95	205	189
observations				
R-squared	0.001	0.04	0.03	0.05

Table 5. Testing Whether EIU Reports Encompass the WEO

Note: standard errors are in the parentheses. Coefficients different from zero at 5% level are in bold.

Table 6. Testing Whether th	e WEO Encompasses	EIU reports
-----------------------------	-------------------	-------------

	Before	After SDDS	Before SDDS	After SDDS
	SDDS		(same month)	(same month)
ß	0.22	0.05	0.08	-0.08
$\mathcal{P}0$	(0.16)	(0.21)	(0.24)	(0.26)
ß.	0.74	0.81	0.52	0.69
P_1	(0.17)	(0.21)	(0.25)	(0.40)
No. of obs.	88	65	53	32
R-squared	0.16	0.19	0.08	0.09

Note: IMF forecast error larger than four per cent in the absolute term is not included. Standard errors are in the parentheses.

References:

- 1. Artis, Michael J (1996), "How Accurate are the IMF's Short-Term Forecasts? Another Examination of the World Economic Outlook," International Monetary Fund Working Paper: WP/96/89.
- Balke, Nathan S and D'Ann Petersen (2002), "How Well Does the Beige Book Reflect Economic Activity? Evaluating Qualitative Information Quantitatively," *Journal of Money, Credit, and Banking* 34, pp. 114--136
- 3. Barrionuevo, Jose M (1992), "A Simple Forecasting Accuracy Criterion under Rational Expectations: Evidence from the World Economic Growth Outlook and Time Series Models," International Monetary Fund Working Paper: WP/92/48.
- 4. Batchelor, Roy (2000), "The IMF and OECD versus Consensus Forecasts," London City University Business School Working Paper.
- 5. Batchelor, Roy and Pami Dua (1991), "Blue Chip Rationality Tests," *Journal of Money, Credit and Banking* 23 (4), pp. 692-705.
- 6. Beach, William, Aaron B. Schavey, and Isabel M. Isidro (1999), "How Reliable Are IMF Economic Forecasts?" Heritage Foundation Center for Data Analysis Report #99-05.
- 7. Clark, Alastair and John Drage (2000), "International Standards and Codes," *Financial Stability Review*, pp. 162--168.
- 8. Davies, Anthony and Kajal Lahiri (1995), "A New Framework for Analyzing Survey Forecasts Using Three-Dimensional Panel Data," *Journal of Econometrics* 68(1), pp. 205-227.
- 9. De Masi, Paula (1996), "The Difficult Art of Economic Forecasting," *Finance and Development* 33, pp. 29--31.
- 10. Faust, J., J.H Rogers, and J.H. Wright (2003), "News and Noise in G-7 GDP Announcements," Working Paper No. 690, Board of Governors of the Federal Reserve System.
- 11. Fair, Ray, and Robert Shiller (1990), "Comparing Information in Forecast from Econometric Models," *American Economic Review* 80 (3), pp. 375--389.
- 12. Gavin, William T and Rachel J Mandal (2001), "Forecasting Inflation and Growth: Do Private Forecasts Match Those of Policymakers?" *Federal Reserve Bank of St. Louis Review* 83(3), pp. 11-19.
- 13. Graham, John R. (1996), "Is a Group of Economists Better Than One? Than None?" *Journal of Business* 69 (2), pp. 193--232.
- 14. Juhn, Grace and Prakash Loungani (2002), "Further Cross-Country Evidence on the Accuracy of the Private Sector's Output Forecasts," *IMF Staff Papers* 49(1), pp. 49--64.
- 15. Lyons, Richard (2001), The Microstructure Approach to Exchange Rates, the MIT Press.
- 16. Obstfeld, Maurice (1994), "The Logic of Currency Crises," NBER Working Paper 4640.
- 17. Peterson, Steven P (2001), "Rational Bias in Yield Curve Forecasts," *Review of Economics and Statistics* 83(3), pp. 457--64.
- 18. Swidler, Steve, and David Ketcher (1990), "Economic Forecasts, Rationality, and the Processing of New Information over Time," *Journal of Money, Credit and Banking* 22 (1), pp. 65--76.