Disclosure Standards and Market Efficiency:
Evidence from Analysts' Forecasts

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Revised, December 2006

Abstract

This paper studies whether recent international transparency initiatives affect information accuracy and dispersion. I show that the impact of these initiatives is limited because public disclosure crowds out private investments in information. I first develop a theoretical model of the incentive to invest in information and the impact of public disclosure. I then analyze stock market analysts' forecasts for thirty developing economies for the period 1990-2004. I find that disclosure standards enhance forecast accuracy directly but at the same time reduce the number of analysts per stock (proxy for private information investments). The net effect of disclosure standards thus ranges from weak to nonexistent.

JEL Classification Codes: F3, G1

Key Words: Disclosure Standards, Analyst Forecast, Public Information, Private Information, International Financial Architecture

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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 on the opacity of financial, corporate and government finances in the region (e.g. Goldstein, 1998). The conclusion drawn by organizations like the International Monetary Fund, the World Bank, and the Bank for International Settlements 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 Fund 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 to further promote the promulgation of standards and codes. These organizations all argued that the implementation of internationally accepted economic, financial, and statistical standards would strengthen domestic financial systems by encouraging sound regulation and supervision, greater market discipline, and more efficient and robust institutions, markets, and infrastructure. They further asserted 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 and contagion.

The logic for these initiatives has not gone undisputed. There is still active debate over what caused the Asian crisis and specifically about whether inadequate transparency was really to blame. Furman and Stiglitz (1998), Morris and Shin (2002), and Morris, Shin and Tong (2006), among others, have raised questions about the conventional wisdom and suggested that there are circumstances where greater transparency may be destabilizing rather than stabilizing. One possible reason for this is that transparency may result in the provision of too much information, actually increasing volatility. Another is that when public information serves as a focal point for the beliefs of a group, noisy public information can precipitate destabilizing reactions.

The generality of these objections, which tend to be based on special cases, remains an open question. In addition, previous authors treated private investments in information as exogenous or predetermined, whereas in the real world agents decide how much to invest in acquiring and processing information. In this paper I attempt to address both limitations of the extant literature. I treat private investments in information as an endogenous variable. And I conduct systemic tests designed to determine the generality of the argument that international initiatives intended to promote the public provision of information may be counterproductive.

For present purposes, I define transparency as the precision of public information. According to this definition, more transparency means that public information is more precise. I examine the effect of transparency by focusing on the interaction between public information availability and private information acquisition. A theoretical model that studies strategically interacting agents provides the analytical framework. In this model, owing to herding among agents, the crowding out between public information and private information is more than one-to-one. So the net influence of transparency on information accuracy can be very weak or even negative. This analysis thus shows that there is no presumption that additional public information must be efficiency enhancing.

I then address the questions empirically. The tests consider how international standards affect analysts' forecasts of listed companies' earnings, where the accuracy (dispersion) of these forecasts is used as a measure of information accuracy (dispersion). This is in contrast to previous empirical work on transparency, which has used sovereign bond spreads and country credit ratings as measures of information efficiency. I argue that analysts' forecasting efficiency is a better measure of information efficiency, since forecast accuracy directly measures the gap between the anticipated and actual outcomes, whereas previous measures do not. Moreover, the variable being forecast - firms' earnings - is consequential; for equity pricing, firms' earnings represent the core of fundamental value. Those doing the forecasting have a stake in doing it well: their jobs are on the line. This contrasts with surveys of expectations of macroeconomic variables in which the people filling out the surveys are typically not being judged personally on the adequacy of their answers. [1]

A variety of different disclosure standards and codes might be analyzed. In this study I focus on the SDDS. The International Monetary Fund established the SDDS in 1996 with the aim of enhancing the operation of international financial markets through the broader public dissemination of economic and financial data. The SDDS considers four dimensions of data dissemination: the comprehensiveness of the data, public access to this information, the integrity of the information provided, and data quality. The SDSS covers data for four sectors: the real sector, the public sector, the financial sector, and the external sector.

The SDDS is included in this study because it is designed to promote the timely and accurate disclosure of macroeconomic variables that could affect firms' profits and analysts' forecasts. O'Brien (1994) shows that macroeconomic news that arrives during a year explains a significant portion of the time variation in that year's corporate earnings. Moreover, macroeconomic news that arrives after analysts have made current-year earnings forecasts is also reflected in their forecast errors. Chordia and Shivakumar (2005) further show that macroeconomic variables account for nearly half of the variation in firms' earnings changes. Reilly and Brown (2003), a practical guide for stock analysts, therefore argues that the forecasting of aggregate macroeconomic conditions is necessarily the first step in forecasting firms' earnings.[2]

Macroeconomic factors become even more important when analysts examine stocks in emerging markets. Previous empirical studies, such as Chan and Hameed (2006), find that stock analysts

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[1] Examples of surveys of expectations on macroeconomic indicators include *Currency Forecasters' Digest* in Chinn and Frankel (1994), and *Blue Chip Economic Indicators* in Laster, Bennett and Geoum (1999).

[2] As shown in Piotroski and Roulstone (2004), analysts' reports primarily facilitate the incorporation of industry and market level information into prices, while insiders' activities contribute primarily firm-specific information.

predominantly process market-wide information (rather than firm-specific information) in developing countries.[3] One interpretation is that it is more difficult to collect firm-specific information in less developed countries, so that stock analysts rely more on economy-wide aggregates, which consequently dominate their forecasts. A related interpretation, due to Morck, Yeung and Yu (2000), is that weak property rights discourage information arbitrage in developing countries and thereby limit the incorporation of firm-specific information into the stock prices.[4] Consistent with such conjectures, my findings in this study confirm that SDDS implementation has significant direct impact on analyst forecast accuracy and dispersion.

A goal of this study is to discover how the SDDS affects stock analysts' behavior and specifically how it influences forecast accuracy and the number of analysts per stock. To this end, I analyze forecasts for stocks issued and traded in 30 countries in the period 1990-2004. The key findings are as follows.

First, disclosure standards have limited benefits insofar as standards diminish the incentive for market participants to invest in private information. Instead of complementing private information, public information resulting from disclosure crowds out private information. As public information becomes more accurate, the need for costly investment in the acquisition of private information declines. This "crowding out" reduces the efficacy of the public standards. In the empirical component of the paper, the specific mechanism through which this "crowding out" takes place is the exit of analysts. I show that the number of analysts per stock declines when international standards are adopted, and that this works to diminish the accuracy of average forecasts.

Second, empirical assessments of the impact of disclosure standards on market outcomes will be biased to the extent that they do not control for the impact on the incentives for market participants to

[3] Chan and Hameed (2006) arrive at this finding by examining the relationship between stock price synchronicity and analyst activity in emerging markets.

[4] Morck, Yeung and Yu (2000) also find that stock prices move together more often in developing countries than in developed countries, which suggests that less firm-specific information is produced in emerging markets.

invest in private information. When the number of analysts per stock is excluded from the explanatory variable set, it appears that meeting SDDS specifications has no significant effect on forecast accuracy and dispersion. However, when the number of analysts is included, the direct effect of the SDDS is to reduce forecast error and dispersion.

The contributions of this paper may be summarized as follows: In terms of theory, it considers not only the crowding out effect between public and private information but also how crowding out affects the impact of transparency on information efficiency. While previous work has examined whether public and private information are substitutes or complements, authors usually focus on the impact on market participants' utility or trading price, rather than on information efficiency, which is the focus here. In addition, I extend the model of Morris and Shin (2002) by endogenizing private information production and by studying how the interaction between public and private information affects information dispersion.

On the empirical side, the contribution of the paper is to suggest a new approach to analyzing the effect of transparency. To my knowledge, this is the first paper to attempt to separate empirically the direct and indirect effects of transparency and thus to estimate the degree of crowding out. In addition, the paper addresses an important policy question by examining whether and how disclosure standards work in developing countries.[5]

[5] The effects of transparency could be separated into the uncertainty effect and the incentive effect, as in Geraats (2002). This paper focuses on the uncertainty effect and studies how public disclosure affects information accuracy in financial markets. In future research, it would be worth examining how transparency standards affect authorities' incentives to adopt sound economic policies. Also, in this paper, we do not examine the impact of public disclosure on social welfare. Arguably, it might be less costly for an authority to provide public information than for investors to acquire private information. In this case, public disclosure may reduce the overall social cost on information acquisition, even though the crowding out suggests that it may not improve overall information accuracy.

The remainder of the paper proceeds as follows. Section 2 first reviews the literature on disclosure standards. Section 3 then develops the theoretical analysis. Section 4 describes the data, while Section 5 discusses the empirical models and findings. Section 6 summarizes the conclusions and policy implications.

2. Literature Review

The international community has been actively engaged in promoting the design and adoption of transparency standards since the early 1990s, efforts that accelerated in the wake of the Asian crisis. However, opinion is still divided on whether more transparency will improve stability, information efficiency and social welfare. Furman and Stiglitz (1998) argue that more information will only constitute a mean-preserving spread and result in greater price volatility. Moreover, greater transparency will reduce the dispersion in expectations across individuals, and cause any information that they receive to have a larger effect on their beliefs – and hence on market conditions – even when the information in question is just unfounded noise. In addition, Morris and Shin (2002) examine the impact of transparency by focusing on the coordination motive arising from strategic complementarities in agents' actions. They show that when individuals have private information, the welfare effect of increased public disclosure is ambiguous. Specifically, the greater the precision of private information, the more likely it is that increased provision of public information lowers social welfare. These two papers thus reach the same conclusion: greater transparency may be counterproductive insofar as the impact of public information is too large.

Empirical work to date has, however, provided little support for these objections. Glennerster and Shin (2003) look at spreads on the sovereign bonds of emerging markets and conclude that SDDS fulfillment reduces spreads for countries with low initial transparency. Gelos and Wei (2005) examine how disclosure standards affect international portfolio investment; they find that emerging market equity funds hold fewer assets in less transparent countries, and that herding among funds is less prevalent in more transparent countries.

Glennerster and Shin (2003) contend that transparency reduces investors' perceived risk and thus the bond spread. In practice, however, the bond spread depends on many other factors that are not directly related to transparency, such as a country's interest rates and inflation rates. For instance, in 2003 and 2004, the U.S. interest rate was relatively low. Thus, "search of yields" by international investors caused a significant reduction in emerging markets' bond spreads. And transparency was not the driving force behind this reduction. Fund holdings and sovereign ratings all have a similar problem: They can be greatly affected by macroeconomic variables that are not closely related to transparency.

To examine transparency effects, we should use variables directly measuring the gap between the expectation of economic fundamentals and their true values, rather than ones that measure whether fundamentals are good or not. For example, if we could construct a variable that records the gap between investors' perceived bond default rate and the actual default rate, then this variable will measure transparency's effect better than the bond spread. The latter measures the perceived default rate, rather than the gap between perceived and actual defaults.

Expectations tend to be unobservable and difficult to measure. Therefore, this paper looks at some economic variables related to market outcomes, such as firms' earnings per share (EPS). An advantage of focusing on this variable is that analyst expectations (as well as actual outcomes) are available. Moreover, these variables are closely related to fiscal and monetary policies, international standards, and global capital flows. Since firms' earnings are affected by macroeconomic policies, more transparent policies can help analysts and investors forecast firms' earnings more accurately. Economic variables such as EPS can also play a crucial role in international investors' decisions on whether to purchase a firm's stock or set up a joint venture.

The accounting literature has also examined the impact of the number of analysts per stock on forecast accuracy. The model implicitly informing these studies is one in which the equilibrium number of analysts is determined by supply and demand. Lang and Lundholm (1996) argue that if it is less costly to receive information from a firm than from other sources, then additional transparency may shift the supply curve for analysts to the right. However, the effect of additional transparency on the demand for analysts is more complicated and relies on the role of analysts. If analysts are effective information intermediaries—information flows first from the firm to the analysts, who then process it and transmit it to the capital market—then more firm-provided information gives analysts more resources to distribute valuable reports. In this situation, the demand for analysts will rise. However, if analysts are information providers who need to compete with firm-provided disclosures made directly to investors, then more firm-provided information will substitute for analysts' reports. In this case, the demand for analysts will decline. Empirically, more corporate disclosure tends to increase analyst following, as shown in Lang and Lundholm (1996). Hope (2003) further finds that as analyst following rises, forecast accuracy increases. Note that these studies focus more on the availability of firm-specific information to outsiders, and less on the availability of market or sector-wide information.[6] Moreover, they tend to rely on cross-country variation rather than time variation in corporate transparency.

Given this, in this paper I ask whether international disclosure standards help analysts improve their forecasts. The accuracy and dispersion of forecasts will offer direct evidence on the influence of such standards.

3. Theoretical Model

This section presents a model to explain the crowding out effect between public and private information, and to investigate how the crowding out affects information accuracy and dispersion.

3.1. Model

Previous work has placed particular emphasis on the herding and peer effects among market players. Examples include Banerjee (1992), Bikhchandani, Hirshleifer and Welch (1992) and Cao and Hirshleifer

[6] Bushman, Piotroski and Smith (2004), for example, examine five aspects of corporate reporting: financial disclosure intensity, governance disclosure intensity, the accounting principles used to measure financial disclosures, timeliness of financial disclosures, and the audit quality of financial disclosures.

(2000). So in the present study, the way in which public and private information interact when herding effects exist, and how the interaction affects information accuracy and dispersion, are examined.

The starting point is the work of Morris and Shin (2002), who develop a strategic interaction model to study the social value of public information. Morris and Shin (2002) provide a useful model for the following two reasons: First, their model is a simple static coordination model, and does not depend on the fine details of the timing structure that exists in the previous herding literature. Second, their model has a unique equilibrium, so is suitable for comparative analysis. However, Morris and Shin (2002) treat private information acquisition as exogenous or pre-determined, and do not explicitly study information dispersion.

Morris and Shin's (2002) model is adapted in two ways: First, their model is extended by endogenizing the production of private information as dependent on the precision of public information. It turns out that the net influence of public information on information accuracy can be negative for a much boarder range of parameters than that in Morris and Shin (2002). Second, how the crowding out between public and private information affects information dispersion is examined. When public information is not precise, I find that the crowding out effect will greatly shrink the influence of public information on information dispersion.

We now start with the assumptions articulated in Morris and Shin (2002). Suppose there is a continuum of agents, indexed by the unit interval [0, 1]. Agent *i* chooses an action a_i to maximize his payoff function

$$u_i(a_i,\theta) \equiv -(1-r)(a_i-\theta)^2 - r(L_i-\overline{L}) \tag{1}$$

where $0 < r < 1, L_i \equiv \int_0^1 (a_j - a_i)^2 dj$, and $\overline{L} \equiv \int_0^1 L_j dj$. The payoff function has two components. The first is a standard quadratic payoff in the distance between his action a_i and the unobservable underlying state θ. The second component is the "beauty contest" term, which provides the motivation for herding. The parameter *r* gives the weight on the second-guessing incentive.

Agent i receives both public information $y = \theta + \eta$, and private information $x_i = \theta + \varepsilon_i$. η is normally distributed with mean zero and precision α (i.e., $\frac{1}{Var[\eta]}$). ε_i is also normally distributed, independent of η and ε_j, with mean zero and precision β (i.e., $\frac{1}{Var[\varepsilon_i]}$). Morris and Shin (2002) argue that when $\alpha < \beta(1-r)(2r-1)$, social welfare will decrease as α increases, where the social welfare is $W \equiv \frac{1}{1-r}\int_0^1 u_i(a_i,\theta)di = -\int_0^1 (a_i-\theta)^2 di$.

Now let us define information accuracy

$$Accuracy \equiv E\left[-(\hat{a}_i - \theta)^2\right] \tag{2}$$

and information dispersion

$$Dispersion \equiv \left(E\left[\int_0^1 (a_i - \bar{a})^2 d_i\right]\right)^{0.5} \tag{3}$$

where $\bar{a}$ is the average of a_i. In the equilibrium, equation (3) becomes

$$Dispersion = \frac{\sqrt{\beta}(1-r)}{\alpha + \beta(1-r)}. \tag{4}$$

However, in Morris and Shin (2002), β is treated as exogenous. Below I will relax this assumption, and extend their model by endogenizing the acquisition of private information. Suppose that private information acquisition is costly and the cost function is $C_i = \phi\beta_i$ for some $\phi > 0$. The payoff function in equation (1) thus becomes

$$V(\beta_i) \equiv E\left[u_i(a_i,\theta)\right] - C = E\left[-(1-r)(a_i-\theta)^2 - r\left(L_i - \bar{L}\right)\right] - \phi\beta_i \tag{5}$$

which includes both the benefit and the cost of acquiring higher β_i.

As shown in the Appendix, the payoff-maximizing β in the equilibrium turns out to be

$$\hat{\beta} = \frac{1}{\sqrt{\phi}} - \frac{\alpha}{1-r} . \tag{6}$$

Therefore, unless $r = 0$, the crowding out between public and private information is greater than one-to-one.

In the equilibrium, we also have

$$Accuracy = -\sqrt{\phi} - \frac{\alpha r \phi}{(1-r)^2} . \tag{7}$$

In this way, higher public information precision will decrease information accuracy.[7] Moreover, in the equilibrium, information dispersion takes the form

$$Dispersion = \sqrt{\phi^{0.5} - \frac{\phi\alpha}{1-r}} . \tag{8}$$

Therefore, higher precision of public information lowers information dispersion. But, this effect may be smaller or larger than if no crowding out existed, depending on whether $\alpha < (0.5\phi^{-0.5})(1-r)$. The intuition is that higher α lowers $\hat{\beta}$. And when $\hat{\beta}$ decreases, the dispersion could go up or down, depending on the relative magnitude of α and $\hat{\beta}$.

3.2. Testable Implications

To test the theoretical results derived above, the following three empirical models are proposed. The first empirical model is

$$\hat{\beta} = \pi_{10} + \pi_{11}\alpha + \nu_1$$

where ν_1 is a disturbance term. The theoretical model suggests that $\hat{\beta}$ will be smaller when α is larger (the crowding out effect). So the first null hypothesis is $\pi_{11} < 0$.

The second empirical model examines the net impact of α on information accuracy

$$E\left[-(\hat{a}_i - \theta)^2\right] = \pi_{20} + \pi_{21}\alpha + \pi_{22}\hat{\beta}(\alpha) + \nu_2 .$$

[7] If the cost C is a convex function of β, then higher α may have a net positive effect on information accuracy.

To test whether the net impact is zero, the second null hypothesis is $\pi_{21} + \pi_{22} \frac{\partial \hat{\beta}}{\partial \alpha} = 0$. Note that the first (second) term is the direct (indirect) effect.

The last empirical model is related to information dispersion

$$\left(E\left[\int_0^1 \left(a_i - \overline{a} \right)^2 d_i \right] \right)^{0.5} = \pi_{30} + \pi_{31}\alpha + \pi_{32}\hat{\beta}(\alpha) + v_3.$$

The theoretical model suggests that π_{32} can be either positive or negative, depending on whether $\alpha < \left(0.5\phi^{-0.5}\right)\left(1 - r\right)$. The last null hypothesis then is $\pi_{32} = 0$. It tests whether the indirect effect of disclosure on information dispersion is zero.

I now test these hypotheses by examining earnings forecasts of stock analysts. I use analyst forecasts for the following reasons. First, international standards are designed to help global investors understand local markets and to facilitate cross-board capital flows. Analysts' forecasts constitute an important channel through which international investors acquire information about local stock markets. If the accuracy of analysts' forecasts does not improve after transparency reforms, then there may be reason to doubt the claim that such reforms will significantly enhance the quality and quantity of information available to international investors. Second, the accuracy of analysts' forecasts is closely related to the transparency of government policies. To forecast a firm's earnings, it is necessary to understand the economic policies of the country in which it operates. Finally, and critically for present purposes, the stock analyst data records the exit and entry of analysts for a certain stock, which helps us to estimate the crowding effect by looking at the analyst number for a stock.

It is worth noting that Morris and Shin's model fits reasonably well with the forecasting profession. The financial press has frequently provided anecdotal stories about herding in this profession (e.g. Nocera and Kover 1997). A number of theories have then been proposed to explain the herding behavior, such as the informational externality theory (Banerjee (1992)) and the principal-agent payoff externality theory (Scharfstein and Stein (1990) and Trueman (1994)). According to the principal-agent theory, analysts' concern for reputation can lead them to ignore private information and imitate the actions of other analysts so that investors can not learn about their true abilities. Empirical work has also provided strong evidence of herding behavior, such as Graham (1999), Welch (2000), and Hong, Kubik, and Solomon (2000). Graham (1999) finds that an analyst is likely to herd on *Value Line*'s recommendation if his reputation is high or if his ability is low. Welch (2000) shows that herding towards the consensus is not caused by fundamental information, which is consistent with models where analysts herd based on little or no information. Hong et. al. (2000) study the relationship between analysts' career outcomes and their forecast boldness (i.e., forecasts that differ markedly from the consensus). They find that analysts are less likely to be promoted when they make relatively bold forecasts. They also find that being bold and relatively inaccurate leads to even worse future career outcomes; however, being bold and relatively accurate does not significantly improve an analyst's future career prospects. Therefore, career concerns give analysts strong incentives to herd.

Analysts may have other incentives as well. For instance, as shown in Hong and Kubik (2003), an analyst may issue optimistic forecasts to generate underwriting business and trading commissions. Morris and Shin (2002) capture the payoffs to analysts for accuracy and herding, but not the payoffs for optimistic forecasts. One may modify the theoretical model to capture various payoffs to analysts. But the key prediction in this paper – additional public information reduces the acquisition of costly private information – is unlikely to be altered after the modification, even though there may be some quantitative differences.

4. Data and Variables

4.1. Data Description

Stock analyst forecasting data were obtained from the Institutional Brokers Estimates System (IBES) database. This database contains analyst-by-analyst estimates for companies in 60 countries for more than 15 years. Variables include company name, data type indicator (e.g., earnings per share), forecast period indicator, broker and analyst code, estimate date, estimate value, actual reported value, etc. Created in the 1970s, IBES now covers over 18,000 companies in 60 countries—more than any other source. In addition, its list of contributors includes more than 7,000 financial analysts from over 1,000 institutions. The accounting research, such as Hope (2003), has relied on the IBES dataset heavily.

Because of the broad coverage of IBES, it is commonly assumed that the number of analysts covered by IBES for a stock is the actual number of analysts who follow that stock. However, before adopting this assumption, some characteristics of the IBES database should be examined to determine whether they affect the results. According to Rajan and Servaes (1997), IBES collects all forecasts from analysts who agree to provide their estimates in return for free use of IBES products. Some biases may therefore enter into IBES's choice of analysts. For example, it may be easier for IBES to obtain forecasts from analysts of the major brokerage houses than from those of small brokerages in remote areas. The former, in turn, may be more likely to ignore small firms trading on regional exchanges. In this case, there are two reasons why a specific firm may not be followed: Either analysts deem the firm unworthy of being followed, or IBES does not receive forecasts from the analysts most likely to follow the firm. Rajan and Servaes (1997) focus on the analyst's following of IPOs, employing Heckman's (1979) selection model to correct for the selection bias in the case where there is no record of analyst following for an IPO.

This selection bias problem is less relevant in the case of my study, which focuses on the forecast accuracy for a stock already recorded in the IBES database, rather than on whether a stock will be covered by IBES. Moreover, I am concerned with how forecast accuracy and dispersion may affect domestic and international investors' behavior. For many investors, IBES real-time and historical forecasting data are important sources for forecasting data, especially for international stocks. If one analyst's forecast is not included in the IBES database, then his/her forecast has much less chance of being known and of affecting investors' market expectations and behavior.

Data on SDDS fulfillment were obtained from the website of the IMF, which records the dates when a country subscribed to the SDDS, began posting data, and met all SDDS requirements. This study focuses on the date at which a country met all requirements (see Table 1). When these are satisfied, a country is said to have fulfilled the requirements of the SDDS.

In what follows I examine forecasting data for stocks in 30 developing countries between 1990 and 2004. Stocks from developed countries are excluded, because they have far more stocks than other markets. If included, they might dominate the estimates, making it difficult to estimate the effects of transparency on developing economies. Markets in which fewer than 10 stocks were covered, such as Latvia, are also excluded from the sample.

4.2. Variables

4.2.1. Dependent variables

- Number of analysts

Analysts sometimes provide multiple-period forecasts of earnings per share. For example, IBM's annual accounting year ends in December 31. For accounting year 2000, analysts may give estimates back in 1999 (a two-year forecasting horizon), and 2000 (a one-year forecasting horizon). In the empirical works that follows I will focus on the one-year horizon. Thus, for every accounting year of IBM, the number of analysts who have given forecasts for the corporation for that year is calculated.

- Forecast dispersion and error

Forecast dispersion is based on the sample standard deviation of forecasts for a stock in an accounting year. To facilitate cross-country comparison, the sample standard deviation divided by the absolute value of the mean earnings forecast is used as the measure of dispersion.

Forecast error is defined in the following manner:

$$Forecast\ Error(t) = \left| \frac{Estimated\ Earnings(t) - Actual(t)}{Actual(t)} \right|$$

For the accounting year ending in December, some analysts provide forecasts in March, and some provide these in November. Intuitively, the estimates offered in November will have smaller forecast errors. To control for this forecasting-time effect, I regress the forecast error on the time difference from the forecasting month to the end of the accounting year.[8] I do this using a pooled regression for all stocks over the whole sample period. For each stock per accounting year, the mean of the residuals from the above regression is calculated as the average forecast error.

4.2.2. Transparency variable

My measure of SDDS fulfillment equals 1 when a country meets all the requirements of the SDDS, and zero otherwise. Note that we are estimating the average forecast error for each stock per accounting year. The data base tells me the date when the first analyst's estimate is provided for a given accounting year for each stock. (Usually this will be a date in March or April.) If the SDDS is fulfilled at that time, I record SDDS as 1 for that accounting year; otherwise, I record 0. Of course, the SDDS can be implemented in the middle of the year, after the first estimate of earnings per share has been given. This may raise some concerns about a time discrepancy, i.e., t in the regression model is in the year frequency, but the implementation of the SDDS is in daily frequency.

As a robustness check, I replace the average forecast error over a year in the regression model with the forecast error for each single estimate. In this case the SDDS dummy is constructed by comparing the SDDS fulfillment date with the forecasting date. This robustness check yields similar results for SDDS implementation. Another robustness check is performed: SDDS is recorded as 1 if SDDS implementation is completed before July 1st, and as 0 otherwise. Again, the empirical results for the SDDS are similar.

4.2.3. Control variables

Earnings surprise. This is the absolute value of the percentage change in the actual earnings per share (in dollar terms). The earnings surprise is included to control for the fact that when earnings surprise is high, forecast error is also likely to be high.

Loss. This is a dummy equaling one when a firm has negative earnings in the current period and zero otherwise. In the following empirical models, *Loss* is lagged by a year.

[8] To reduce the influence of outliers, forecast errors belonging to the highest 2% of the sample are replaced with the threshold value for the top 2%.

Macroeconomic variables. These include GDP growth rate, inflation rate, stock market capitalization over GDP, and the number of listed domestic stocks in a country (square root). Year dummies are also included.

5. Empirical Models and Results

The first empirical model, of the determinants of forecast errors, is

$$\begin{aligned} Mean\,Forecast\,Error_{ijt} &= \omega_{11} + \omega_{12} Transparency_{jt} + \omega_{13} Analyst\ Number_{ijt} + \omega_{14} Surprise_{ijt} + \\ &\omega_{15} Loss_{ij,t-1} + \omega_{16} Macro_{jt} + \omega_{17} Time_t + v_{i1} + \varepsilon_{1,ijt} \end{aligned}$$

where *i*, *j* and *t* stands for stock *i* in country *j* at time *t*. v_{i1} is the fixed effect for stock *i*. Annual data are used in all estimations. Note that the dependent variable is the average of the absolute distances between forecasts and the actual value, rather than the absolute distance between the average forecast and the actual value. Therefore, the value of the dependent variable does not necessarily decrease as the number of analysts increases.

The second model studies the dispersion of analyst forecasts:[9]

$$\begin{aligned} Dispersion_{ijt} &= \omega_{21} + \omega_{22} Transparency_{jt} + \omega_{23} Analyst\ Number_{ijt} + \omega_{24} Surprise_{ijt} + \omega_{25} Loss_{ij,t-1} + \\ &\omega_{26} Macro_{jt} + \omega_{27} Time_t + v_{i2} + \varepsilon_{2,ijt} \end{aligned}$$

Finally, the third model studies the analyst following (i.e., the number of analysts):

$$Analyst\ Number_{ijt} = \omega_{31} + \omega_{32} Transparency_{jt} + \omega_{33} Loss_{ij,t-1} + \omega_{34} Macro_{jt} + \omega_{35} Time_t + v_{i3} + \varepsilon_{3,ijt}.$$

$Transparency$ is the proxy for the precision of public information (α in the theoretical model). *Analyst number* is the proxy for market participants' investments in acquiring private information (β in the theoretical model), which has been used in the accounting and finance literature (e.g. Bushman, Piotroski and Smith (2005)). These three models are estimated separately for SDDS implementation. The empirical results are as follows.

[9] Simulation results show that the sample standard deviation does not necessarily decrease as the sample size increases. Therefore, the dispersion need not decrease as the number of analysts increases.

5.1. SDDS Implementation

The benchmark results for the SDDS are in Table 2 though 4. Table 2 presents the direct and net effects of the SDDS on the forecast error in developing countries, while Table 3 shows the effect of the SDDS on analyst following in developing countries. SDDS implementation changes over time. Thus, it is reasonable to estimate a fixed effects model (over each stock) to analyze the effects of the SDDS. Our sample period is expanded to cover 1990-2004. The fixed effects model will not work, however, for countries that never fulfill the SDDS, since for them the SDDS dummy always takes a value of zero.

The estimates suggest that SDDS fulfillment directly reduces the forecast error. The estimated value of the direct effect, at -0.14, is significantly different from zero at the 95% confidence level. This is consistent with the view that SDDS fulfillment ensures the more timely and accurate provision of information on macroeconomic variables; since macroeconomic variables affect firms' operation, analysts' forecasts of company earnings will be more accurate as a result. Since the median forecast error for each stock is 0.7, with SDDS fulfillment the forecast error drops by 20%.

The fixed effects model (Table 2) confirms the result that higher analyst following reduces the forecast error. The coefficient on the square root of the number of analysts is -0.11 and different from zero at the 1% significance level. When the analyst number (square root) increases by 1, in other words, the forecast error drop by 0.11, which is 16% of the initial error. In the sample, the number of analysts per stock varies from 1 to 28. Because an additional analyst where there was previously only one is very unlikely to have the same influence as where there were already 20 analysts, the square root is used to control for the possible diminishing marginal effect of additional analysts in Table 2. Using the number of analysts instead of the square root yields similar results.

But this is only the direct effect. The net influence of the SDDS on forecast accuracy, including both the direct and indirect effects, is insignificantly different from zero. The net effect is an aggregate of both the direct effect of the SDDS (-0.14 as above), and the indirect effect owing to the drop of analyst number after SDDS fulfillment. The net effect of the SDDS is presented in the second column of Table

2. There, the number of analysts is excluded from the set of explanatory variables. The coefficient on the SDDS will be a measure of this net effect, which is –0.11 and different from zero only at the 89% confidence level. Thus, the net effect is only 80% of the direct effect, owing to the indirect effect working in the opposite direction.

Table 3 presents additional analysis of the indirect effect. The results show that the SDDS is associated with a reduced analyst following (square root). After SDDS fulfillment, 20% of analysts will leave the forecasting market. Recall that the average number of analysts, for a given stock, is 4 in developing countries. The 20% fall means, roughly speaking, that there will be one less analyst per stock. The indirect effect of the SDDS then is the multiplication of the effect of analyst number on forecast error (-0.11 in Table 2) and the effect of the SDDS on analyst number (-0.22 in Table 3). The indirect effect measured in this way is similar to that in the previous paragraph.

Above, a block recursive model was used, where some control variables X affect the number of analysts, and then some control variables Z and the number of analysts affect forecast error, with no feedback from forecast error to analyst following. Here, the sensibility of that assumption is considered. If the accuracy of forecasts in actuality affects the number of analysts, then simultaneity and bias may exist in the estimation. The literature has been divided on whether to treat the number of analysts as exogenous in the estimation for analyst forecast error. Most previous works, such as those by Hope (2003), and Berger and Hann (2003), treat analyst following as exogenous in estimating its effect on forecast accuracy. One possible argument for them is that the number of analysts is predetermined relatively to forecast error. An analyst decides to start forecasting for a stock before giving an estimate. Moreover, since the actual value may not come out until the firm's annual report is out, which can be up to 8 months or more after the estimate is already given by the analyst, the accuracy of the estimate will not be known at the time of the forecasting.

There are, however, a couple of papers that treat analyst following as endogenous to forecast accuracy. Alford and Berger (1999), followed by Lang, Lins and Miller (2003), take this approach. Since there may be shocks that affect both analyst following and forecast accuracy at the same time, considering analyst following as endogenous to forecast accuracy is not unreasonable. They propose instrument variables for analyst following, such as the amount of new equity issued that year for a given stock, the fraction of the company's sales in a regulated industry, the number of industry segments the firm's business is in, and the Herfindale index (the sum of squared proportions) for the company's sales across its industry segments. However, these instruments may not be good instruments in that they may also affect forecast error. For this reason, these instruments are not used here.

Whether the analyst following is treated as exogenous or endogenous, the conclusion, in the above papers, is the same: As analyst following goes up, forecast accuracy will increase. Alford and Berger (1999) find that the effect of analyst following is bigger with instrument variables than without instrument variables. This positive connection is supported by two theoretical explanations. Lys and Soo (1995) argue that as the number of analysts goes up, the competition among analysts will intensify and lead them to put more effort into accuracy. Alford and Berger (1999) argue that as the number of analysts goes up, expenditure on information acquisition increases on aggregate, and the amount of information uncovered about a company will go up on aggregate, which will increase forecast accuracy on average.

In this paper, the one-year lagged analyst number for each stock is used as the instrumental variable. The lagged analyst number is correlated with the current analyst number, but not correlated with the shock to the current forecast error. After applying the instrumental variable in the forecast error estimation, and performing the Hausman test for simultaneity, the null hypothesis that the analyst number is exogenous to forecast error cannot be rejected based on the results achieved.[10]

Table 4 analyzes the impact of the SDDS on information dispersion. Its direct effect is -0.06, significantly different from zero at eight percent level (first column). The net effect of the SDDS is -0.04

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[10] In the first stage estimation, the estimated coefficient of the lagged analyst number is 0.59, different from zero at 1% significance level. Moreover, the overall R-square of the first stage estimation is as high as 0.62.

and different from zero at 24% significance level (second column). The indirect effect thus is around 33% of the direct effect. More analysts per stock will decrease forecast dispersion (first column), which is consistent with the theoretical argument that when $\alpha < \left(0.5\phi^{-0.5}\right)\left(1-r\right)$, the effect of α on dispersion will become smaller after the crowding out.

5.2. Control Variables

Most of the control variables enter as expected. Table 2 shows that earnings surprise increases forecast error, as expected (If the earnings change significantly from year to year, it will be more difficult for analysts to forecast.) A *Loss* will discourage analyst following (Table 3). This result is plausible insofar as analyst bonuses depend on the stock trading commission brought to the brokerage house. The trading commission depends on the stock trading volume and the stock price. When a firm has a loss for the previous period, both its stock price and stock trading volume may drop, which will decrease the trading commission to brokerage houses and discourage analyst following.

5.3. Robustness Checks

To better incorporate macroeconomic information into forecasts, analysts can examine a firm's exposure to macroeconomic fundamentals, such as the correlation between the growth of firm's earnings and the growth of GDP. Higher the correlation, higher the power of the GDP growth rate in explaining firm's earnings. Thus for firms with higher correlation, investors and analysts can infer earnings more accurately from disclosed GDP growth rate, *ceteris paribus*. Then according to the theoretical model, one would see more crowding-out of private information collection for these firms. To test this prediction, I first calculated the absolute correlation between the growth of firm' earnings and the growth of GDP, then I interacted it with the SDDS implementation dummy to test whether firms with higher correlation see larger reduction in analyst coverage.[11] The results are reported in Table 5. Again, SDDS

[11] Both the earnings and the GDP are measured in constant local currency. GDP growth rate is chosen to represent macroeconomic fundamentals in that it is the most heavily forecasted macroeconomic variable. Note that only firms

implementation reduces analyst coverage. Moreover, firms with higher exposure to macroeconomic fundamentals see larger reduction in analyst following.

One might argue that the reduction in analyst coverage was mainly due to the retreat of American stock analysts from emerging markets. Wall Street brokerage houses had slashed staff after the burst of the dot-com bubble in mid-2000 and the subsequent analyst scandals. Some laid-off American analysts covered both US and emerging markets, particularly along the same industry line. When they were laid off, analyst coverage for emerging markets could be reduced too, which was not due to SDDS implementation in emerging markets. Therefore, I examined whether the reduction of analyst coverage in emerging markets was mainly driven by the retreat of American analysts. I first identified analysts that covered both US and non-US stocks from the IBES Broker and Analyst Translations file.[12] I then excluded these analysts and re-estimated Table 3. Reassuringly, the effect of SDDS implementation on analyst coverage remains almost the same.

I also looked at whether adding other characteristics of firms affects the impact on analyst following. I therefore added two more firm-level explanatory variables: past five-year earnings' growth rate, and past five-year earnings' standard deviation. Doing so shrinks the sample size by 50%. Nevertheless, the key results on the effects of the SDDS are not altered significantly.

6. Conclusion

This paper has analyzed the impact of disclosure standards on the information environment. It has provided a heterogeneous-agent model useful for analyzing the potential for private information to be crowded out by public disclosure. This model suggests that disclosure standards which improve agents' access to public information may at the same time weaken market incentives to make costly investments

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with at least five-year IBES coverage are included in the sample so that the correlation calculation will not be significantly affected by just one or two years' observations.

[12] Not all the analysts that cover both US and emerging markets are employed by American brokerage houses. But they are much more likely to be American analysts compared with those that cover only emerging markets.

in the acquisition of private information. The net effect of transparency on quality of expectations and decisions under these conditions can be small, zero, or even negative.

The empirical analysis then focuses on the accuracy and dispersion of stock analysts' forecasts and how these change with SDDS implementation. I find that the direct effects on forecast error and dispersion of SDDS implementation are negative, as expected. However, there are also important indirect effects – operating through the decline in analyst following and consequent reduction in the production of private information when public information becomes more readily available – which are positively associated with forecast error and dispersion. As a result, the overall effect of these disclosure standards ranges from weak to nonexistent.

These findings do not suggest that the disclosure standards on which the international policy community has been focusing in recent years are useless or counterproductive. But they do suggest that the benefits, in terms of improvements in the efficiency of market outcomes, may have been exaggerated. If the goal is to improve the overall information environment, then it is important to complement disclosure standards, which promote the dissemination of public information, with other policy initiatives to, at the same time, encourage investment in the production of private information and minimize crowding out.

Appendix

In this Appendix, I will first briefly describe the model in Morris and Shin (2002), then extend their model by endogenizing private information collection, and finally study how the interaction between public and private information affects information accuracy and dispersion.

1. Model in Morris and Shin (2002)

There is a continuum of agents, indexed by the unit interval [0, 1]. Agent *i* chooses an action a_i to maximize his payoff function

$$u_i(a_i,\theta) \equiv -(1-r)(a_i-\theta)^2 - r\left(L_i - \overline{L}\right) \tag{A.1}$$

where 0<r<1, $L_i \equiv \int_0^1 \left(a_j - a_i\right)^2 dj$, and $\overline{L} \equiv \int_0^1 L_j dj$. $u_i(a_i,\theta)$ has two components: the first one is a quadratic payoff in the distance between a_i and the underlying state θ; and the second one is the "beauty contest" term.

Agent *i* observes both the public signal $y = \theta + \eta$, and his private signal $x_i = \theta + \varepsilon_i$. The noise term η is normally distributed with mean zero and variance $1/\alpha$. ε_i is also normally distributed with mean zero and variance $1/\beta$, independent of η and ε_j.

The first order condition for payoff-maximizing is

$$\hat{a}_i = (1-r)E_i[\theta] + rE_i[\overline{a}] \tag{A.2}$$

where $\overline{a} \equiv \int_0^1 \hat{a}_j dj$ and the expectation operator $E_i[\cdot]$ is conditioned on x_i and y. Consequently, the unique equilibrium action is given by

$$\hat{a}_i = \frac{\beta(1-r)}{\alpha+\beta(1-r)}x_i + \left(1 - \frac{\beta(1-r)}{\alpha+\beta(1-r)}\right)y\ , \quad \textit{for all } i. \tag{A.3}$$

Social welfare, in Morris and Shin (2002), is defined as $W \equiv \frac{1}{1-r}\int_0^1 u_i(a_i,\theta)di = -\int_0^1 (a_i-\theta)^2 di$.

They show that if $\alpha < \beta(1-r)(2r-1)$, higher α will decrease social welfare.

Now let us define information accuracy

$$Accuracy \equiv E\left[-(\hat{a}_i - \theta)^2\right] \tag{A.4}$$

and information dispersion

$$Dispersion \equiv \left(E\left[\int_0^1 (a_i - \overline{a})^2 d_i\right]\right)^{0.5} \tag{A.5}$$

where $\overline{a}$ is the average of a_i. Note that both definitions are absent in Morris and Shin (2002). In the equilibrium, equation (A.5) becomes

$$Dispersion = \frac{\sqrt{\beta}(1-r)}{\alpha + \beta(1-r)}. \tag{A.6}$$

However, in Morris and Shin (2002), β is treated as exogenous. Below I will relax this assumption, and endogenize β as a function of α.

2. The Extension to Morris and Shin (2002)

Assume that private information acquisition is costly and the cost function is $C_i = \phi\beta_i$ for some $\phi > 0$. The payoff function in equation (A.1) thus becomes

$$V(\beta_i) \equiv E\left[u_i(a_i, \theta)\right] - C = E\left[-(1-r)(a_i - \theta)^2 - r\left(L_i - \overline{L}\right)\right] - \phi\beta_i \tag{A.7}$$

which includes both the benefit and the cost of acquiring higher β_i. Agent *i* will choose β_i to maximize his payoff. The level of β_i in the symmetric equilibrium can be obtained through the following two steps: First, the payoff-maximizing $\hat{a}_i$ for agent *i* is solved, given that his private information precision is β_i and that all other agents have the private information precision of $\overline{\beta}$. Second, given $\overline{\beta}$, the payoff-maximizing $\hat{\beta}_i$ is solved for agent *i*. $\hat{\beta}_i$ is then set equal to $\overline{\beta}$ to derive the equilibrium precision $\hat{\beta}$.

Suppose that all agents, other than agent *i*, have the same level of private information precision $\overline{\beta}$, then the optimal action for all agents other than agent *i* is

$$\hat{a}_j = kx_j + (1-k)y\,, \quad for\ j \neq i \tag{A.8}$$

where $k=\dfrac{\bar{\beta}(1-r)}{\alpha+\bar{\beta}(1-r)}$. Meanwhile, given β_i, the first order condition for agent *i* is the same as equation (A.2):

$$\hat{a}_i=(1-r)E_i[\theta]+rE_i[\bar{a}] \tag{A.9}$$

where $E_i[\theta]=\dfrac{\alpha y+\beta_i x_i}{\alpha+\beta_i}$, and $E_i[\bar{a}]=k\dfrac{\alpha y+\beta_i x_i}{\alpha+\beta_i}+(1-k)y$. Combining equations (A.7), (A.8), and (A.9), we obtain

$$V(\beta_i)=-\frac{(1-r)^2(\alpha+\bar{\beta})^2}{(\alpha+\bar{\beta}(1-r))^2(\alpha+\beta_i)}-\frac{r^2\alpha}{(\alpha+\bar{\beta}(1-r))^2}-r\left(\frac{k^2}{\bar{\beta}}+\frac{(1-k)^2}{\alpha}-\bar{L}\right)-\phi\beta_i\,. \tag{A.10}$$

Agent *i* will then choose β_i to maximize $V(\beta_i)$. His choice is determined by the first-order condition:

$$\hat{\beta}_i=\frac{(1-r)(\alpha+\bar{\beta})}{\sqrt{\phi}(\alpha+\bar{\beta}(1-r))}-\alpha. \tag{A.11}$$

Note that we assume $\hat{\beta}_i>0$, which holds as long as $\alpha<(1-r)\phi^{-0.5}$.

To derive the equilibrium $\hat{\beta}$, $\hat{\beta}_i$ is then set equal to $\bar{\beta}$ in equation (A.11). Thus,

$$\hat{\beta}=\hat{\beta}_i=\bar{\beta}=\frac{1}{\sqrt{\phi}}-\frac{\alpha}{1-r}\,. \tag{A.12}$$

Therefore, unless $r=0$, the crowding out between public and private information is greater than one-to-one. Note that if $\alpha>(1-r)\phi^{-0.5}$, then $\hat{\beta}=0$.

3. Information Accuracy and Dispersion

In the equilibrium, we have

$$Accuracy=-\sqrt{\phi}-\frac{\alpha r\phi}{(1-r)^2}\,. \tag{A.13}$$

In this way, higher precision of public information is associated with lower information accuracy. Substituting β in equation (A.6) with $\hat{\beta}$, we further obtain

$$Dispersion = \sqrt{\phi^{0.5} - \frac{\phi\alpha}{1-r}}\,. \qquad \text{(A.14)}$$

Now let us examine how the crowding out between α and $\hat{\beta}$ affects the net impact of α on information dispersion. If there were no crowding out, then according to equation (A.6), the effect of α on dispersion would be

$$\frac{\partial Dispersion}{\partial \alpha} = -\frac{\sqrt{\hat{\beta}}(1-r)}{\left(\alpha + \hat{\beta}(1-r)\right)^2}. \qquad \text{(A.15)}$$

However, if there is crowding out, then

$$\frac{dDispersion}{d\alpha} = -\frac{\sqrt{\hat{\beta}}(1-r)}{\left(\alpha + \hat{\beta}(1-r)\right)^2} + \frac{\partial\left(\dfrac{\sqrt{\hat{\beta}}(1-r)}{\alpha + \hat{\beta}(1-r)}\right)}{\partial \hat{\beta}} \frac{\partial \hat{\beta}}{\partial \alpha} \qquad \text{(A.16)}$$

Compared with equation (A.15), equation (A.16) has an extra term. We could see that if $\partial\left(\hat{\beta}^{0.5}\left(\alpha + \hat{\beta}(1-r)\right)^{-1}\right)/\partial\hat{\beta} < 0$, which holds as long as $\alpha < 0.5(1-r)\phi^{-0.5}$, then the crowding out between α and $\hat{\beta}$ will shrink the overall impact of α on information dispersion. However, if the opposite holds, then the crowding out will actually amplify the impact of α on dispersion.

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Table 1. SDDS Implementation

Developing Economies	SDDS Implementation Date
Argentina	1-Nov-1999
Brazil	14-Mar-2001
Chile	30-Mar-2000
China	
Colombia	9-May-2000
Croatia	30-Mar-2001
Czech Republic	4-Jun-1999
Egypt	31-Jan-2005
Estonia	30-Mar-2000
Greece	8-Nov-2002
Hong Kong, SAR, PRC	12-Jul-2000
Hungary	24-Jan-2000
India	14-Dec-2001
Indonesia	2-Jun-2000
Israel	5-Jun-2000
Korea	1-Nov-1999
Malaysia	1-Sep-2000
Mexico	29-Jun-2000
Morocco	15-Dec-2005
Pakistan	
Peru	15-Jul-1999
Philippines	17-Jan-2001
Poland	2-Mar-2000
Russian Federation	31-Jan-2005
Singapore	30-Jan-2001
Slovenia	7-Jul-2000
South Africa	18-Sep-2000
Thailand	16-May-2000
Turkey	20-Jul-2001
Venezuela	

Source: the IMF

Table 2. Impact of the SDDS on Forecast Error

	(1)	(2)
Number of analysts	-0.11*	
(Square root)	(0.02)	
SDDS implementation	-0.14*	-0.11
	(0.07)	(0.07)
Earnings surprise	0.29*	0.29*
	(0.002)	(0.002)
Loss	-0.88*	-0.84*
	(0.05)	(0.05)
Inflation rate	0.38	0.38
	(0.25)	(0.26)
Number of domestic stocks	-0.77	-0.86
	(0.57)	(0.57)
GDP growth rate	-2.30*	-2.47*
	(0.45)	(0.45)
Stock market capitalization	0.36*	0.36*
over GDP	(0.04)	(0.04)
Constant	-0.40	-0.63
	(0.19)	(0.19)
R-square (within)	0.48	0.48
Observations	29834	29834

Note: Standard errors in parentheses. * indicates significance at 5%. Yearly dummies are included in estimation, though not reported here.

Table 3. Impact of the SDDS on Analyst Number

SDDS implementation	-0.22*
	(0.02)
Loss	-0.38*
	(0.02)
Inflation rate	-0.001
	(0.08)
Number of domestic stocks	0.77*
	(0.18)
GDP growth rate	1.55*
	(0.14)
Stock market capitalization over GDP	0.001
	(0.01)
Constant	2.04
	(0.06)
R-square (within)	0.14
Observations	29834

Note: Standard errors in parentheses. * indicates significance at 5%. Yearly dummies are included in estimation, though not reported here.

Table 4. Effect of the SDDS on Forecast Dispersion

Number of analysts (Square root)	-0.10* (0.01)	
SDDS implementation	-0.06 (0.036)	-0.04 (0.036)
Loss	0.54* (0.03)	0.58* (0.03)
Inflation rate	-0.01 (0.02)	-0.01 (0.02)
Number of domestic stocks	-0.80* (0.27)	-0.87* (0.28)
GDP growth rate	-3.61* (0.21)	-3.74* (0.21)
Stock market capitalization over GDP	0.04* (0.02)	0.04* (0.02)
Constant	1.08 (0.09)	0.84 (0.09)
R-square (within)	0.08	0.08
Observations	26522	26522

Note: Standard errors in parentheses. * indicates significance at 5%.Yearly dummies are included in estimation, though not reported here.

Table 5. Impact of the SDDS on Analyst Number

SDDS implementation	-0.21* (0.03)
SDDS implementation* Correlation between earnings and GDP	-0.17* (0.06)
Loss	-0.40* (0.02)
Inflation rate	-0.02* (0.01)
Number of domestic stocks	0.30 (0.19)
GDP growth rate	1.77* (0.15)
Stock market capitalization over GDP	-0.06* (0.01)
Constant	2.42 (0.06)
R-square (within)	0.15
Observations	25071

Note: Standard errors in parentheses. * indicates significance at 5%. Yearly dummies are included in estimation, though not reported here.