Disclosure Standards and Market Efficiency:
Evidence from Analysts' Forecasts

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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 information accuracy and dispersion. I show that the impact of transparency initiatives may be more limited than often thought to the extent that 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 a panel data set of stock market analysts’ forecasts for sixty countries for the period 1990-2002. I find that disclosure standards enhance forecast accuracy directly but at the same time reduce the number of analysts per stock (the variable that serves as my proxy for private investments in information). The net effect of disclosure standards on forecast accuracy and dispersion thus ranges from weak to nonexistent. The implication is that studies that fail to analyze this crowding out effect may exaggerate the impact of disclosure standards on market outcomes.

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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 at least partly on the opacity of financial, corporate and government finances in the region (see for example 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 General Data Dissemination System and the Special Data Dissemination Standard for countries active on international financial markets. The Fund and 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 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 help to 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) and Morris and Shin (2002), among others, have raised questions about the conventional wisdom and suggested that there are

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2 The Forum was first convened in April 1999 at the initiative of the G7 group.
3 FSF’s Compendium of Standards lists the various economic and financial standards that are important for sound, stable, and well-functioning financial systems, and highlights 12 key standards which it believes to be deserving of priority implementation.
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. The analytical framework is provided by a pair of theoretical models. The first model analyzes the actions of a representative agent who receives public information for free, collects private information for cost, and minimizes the gap between his belief and the true underlying value. It shows that greater availability of public information diminishes the agent’s incentive to assemble private information. Depending on the information cost function form, the net effect of transparency on information accuracy can be zero (with a linear cost function), positive (with a convex cost function) or negative (with a concave cost function). Moreover, the degree of crowding out can be very sensitive to the form of the cost function. Crowding out between public and private information can be one to one (with a linear cost function), less than one to one (with a convex cost function), or more than one to one (with a concave cost function).

The second theoretical model extends the analysis to a continuum of strategically interacting agents. In this model, when the public information is not precise, the crowding out effect will reduce the influence of public information on information dispersion.
Owing to herding among agents, the net influence of transparency on information accuracy can be negative even when the information cost function is linear. 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 for the adequacy of their answers.  

A variety of different disclosure standards and codes might be analyzed. In this study I focus on the Special Data Dissemination Standard (SDDS) and International Accounting Standards (IAS). 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 (coverage, periodicity, and timeliness), public access to this information, the integrity of the information provided, and data quality. The SDSS covers data for four sectors: the real sector (such as national accounts and forward-looking indicators), the public sector (such as government revenue, spending and debt), the financial sector (such as money supply,  

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4 Examples of surveys of expectations on macroeconomic indicators include the ASA-NBER survey in Keane and Runkle (1990), Currency Forecasters’ Digest in Chinn and Frankel (1994), and Blue Chip Economic Indicators in Laster, Bennett and Geoum (1999).
domestic credit, and interest rates), and the external sector (such as international reserves
and external debt).5

The SDDS is included in this study because it is designed to promote the timely and
accurate disclosure of macroeconomic variables that affect firms’ profits and analysts’
forecasts. As stated in Reilly and Brown (2003) – which is written as a practical guide for
stock analysts – the forecasting of aggregate macroeconomic conditions is necessarily the
first step in forecasting firms’ earnings.6 Moreover, previous empirical studies, such as
Chan and Hameed (2002), find that stock analysts predominantly process market-wide
information (rather than firm-specific information) in developing countries.7 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.8 Consistent with such conjectures, my findings in this study confirm
that SDDS implementation has significant direct impact on analyst forecast accuracy and
dispersion.

International accounting standards (IAS) are included in this study because they are
central to the process of encouraging firm-level disclosure -- firms’ financial reports are
public information and thus directly affect analysts’ forecasts. The International
Accounting Standards Board has been developing IAS since the 1980s. IAS cover a
variety of different areas of financial reporting, such as segment reporting and related
party disclosure.9 A motivation for the development and adoption of IAS is the need for
reliable and transparent accounting and financial reporting to support sound decision-

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5 For more details, see http://dsbb.imf.org/Applications/web/sddshome/.
6 This point is discussed on page 452 of Reilly and Brown (2003).
7 Chan and Hameed (2002) arrive at this finding by examining the relationship between the stock price
synchronicity and analyst activity in the emerging markets.
8 Morck, Yeung and Yu (2000) also find that stock prices move together more in developing countries than
in developed countries, which suggests that less firm-specific information is produced in emerging markets.
9 The Appendix II lists various rules in IAS.
making by investors, lenders, and regulatory authorities. Since the Asian crisis, a significant number of additional IAS rules have been developed and promulgated.  

A goal of this study is to discover how the SDDS and IAS affect stock analysts’ behavior and specifically how they influence forecast accuracy and the number of analysts per stock. To this end, I analyze forecasts for some 18,000 stocks issued and traded in 60 countries in the period 1990-2002. The key findings are as follows.

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

Third, crowding out of private information by public information is more severe in developing than developed countries. An interpretation is that public information is in relatively short supply in developing countries, and the degree of crowding out declines as public information becomes more precise.

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

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10 In 1998, G7 Finance Ministers and Central Bank Governors committed themselves to ensuring that private sector institutions in their countries comply with internationally agreed upon principles, standards, and codes of best practice. They called on all countries that participate in global capital markets to similarly commit to compliance with these codes and standards.
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.\footnote{Bushman (1991) studies how the structure of the private information market affects the demand for public disclosure. Instead of looking at the effect on information efficiency, Bushman (1991) looks at traders’ utility function, which depends on the trading price, traders’ risk tolerance, and final wealth after trading. Lundholm (1991), and Alles and Lundholm (1993) take a similar approach.} In addition, this paper seeks to determine not just whether public and private information are substitutes, but also the degree of substitution.\footnote{Verrechia’s (1982) is one of the first papers to study the crowding out effect. Verrechia (1982) focuses on the convex information cost function form, but does not study the degree of crowding out and does not explicitly analyze how information efficiency changes after the crowding out.} Finally, 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 in the equilibrium.

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 how and whether the adoption of transparency standards works in developing countries.

The remainder of the paper proceeds as follows. Section II first reviews the literature on transparency standards. Section III then develops the theoretical analysis. Section IV describes the data, while Section V discusses the empirical models and findings. Section VI 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. The IMF has encouraged its members to subscribe to the \textit{Special Data Dissemination Standard (SDDS)}, which was initiated in early April 1996. Subscription carries a commitment to provide timely information to the IMF in 18 data categories covering four sectors of the economy. Two years later the Fund published its
Code of Good Practices in Fiscal Transparency, which sets out standards for the collection and dissemination of fiscal data and information. The objective of the code is to encourage a well-informed public debate about the design and results of fiscal policy, thereby making governments more accountable. Similarly, the IMF’s Code of Good Practices on Transparency in Monetary and Financial Policies identifies desirable data transparency practices for central banks and other financial agencies. The design of these codes rest on the principle that “monetary and financial policies can be made more effective if the public knows and understands the goals and instruments of policy and if central banks and financial agencies make a credible commitment to meeting them.”

Other international organizations have promulgated related standards. The Basel Committee on Banking Supervision published its Core Principles for Effective Banking Supervision; the International Organization of Securities Commissions (IOSCO) outlined Objectives and Principles for Securities Regulation; the International Accounting Standards Board (IASC) constructed International Accounting Standards (IAS); the International Federation of Accountants proposed International Standards on Auditing; and the World Bank released the standards on insolvency and creditor rights. The IMF and the World Bank also examine a country's observance of the internationally recognized standards and codes listed above in their Reports on the Observance of Standards and Codes (ROSCs). As of the end of October 2003, more than half of the IMF's 184 member countries had completed one or more ROSC modules.

Although the effort to encourage transparency gained momentum in both the official and private sectors following the Asian Crisis, opinion is still divided on whether inadequate transparency was actually to blame for the crisis. Stiglitz (1998) insists that “claims about transparency are just a form of blame shifting. There is no systematic evidence linking lack of transparency to economic crises. The last major banking-cum-currency crises were in Scandinavia – models of transparency. Even if there were, there is no evidence that corruption or transparency were significant problems in all of the East

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14 The code was adopted by the IMF's Interim Committee in September 1999. The Code covers four categories for transparency: (i) clarity of roles, responsibilities and objectives; (ii) open process for formulating and reporting policy decisions; (iii) public availability of information of policies; and (iv) accountability and assurances of integrity. See http://www.imf.org/external/np/exr/facts/mtransp.htm for details.
Asian countries affected by the crisis.” On the other side, Fisher (1998) claims that “[i]n weak financial systems, excessive unhedged foreign borrowing by the domestic private sector, and a lack of transparency about the ties between government, business, and banks have both contributed to the crisis and complicated efforts to defuse it.” Ferguson (1998), a governor of the Federal Reserve System, echoes this view, arguing that in Asian countries, “Standards for the transparency and disclosure of private financial information were extremely lax. Once problems arose, it was difficult for creditors to distinguish good risks from bad, and this caused them to withdraw credit from all borrowers indiscriminately.”

The debate has also found reflection in academic research. Furman and Stiglitz (1998) argue that in a rational expectations model where price equals the expected value of the underlying variable, more information will only constitute a mean-preserving spread and result in greater price volatility. Moreover, greater transparency will flatten the distribution of agents’ priors, 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, following Radner and Stiglitz (1984) it is easy to construct general equilibrium models with imperfect markets in which more information—and hence greater price volatility—leads to lower economic welfare. 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. As they argue, the detrimental effect of public information arises from the fact that the coordination motive entails people placing too much weight on the public signal relative to the weights that would be used by the social planner. Furman and Stiglitz (1998) and Morris and Shin
thus (2002) reach the same conclusion: greater transparency may be counterproductive insofar as the impact of public information is too large.\textsuperscript{15}

Empirical work to date has, however, provided little support to these objections. Glennerster and Shin (2003) look at spreads on the sovereign bonds of emerging markets and conclude that SDDS fulfillment reduces spreads, other things equal, especially for countries with low initial transparency. Christofides, Mulder, and Tiffin (2003) also study whether international standards are relevant to country bond spreads and sovereign ratings. They find that standards are indeed relevant, especially when these cover accounting practices, property rights, and data distribution (SDDS subscription). Gelos and Wei (2002) examine how transparency 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 somewhat less prevalent in more transparent countries.

In Glennerster and Shin (2003), the bond spread is defined as a country’s EMBI portfolio yield over the theoretical US zero coupon curve, where the sovereign yield is set to equate the total net present value of the sovereign risk cash flows to zero. They contend that transparency may reduce investors’ perceived risk and thus the bond spread. For example, if investors can observe the true level of international reserves, they may be able to exit before a potential devaluation by monitoring the level of reserves. In practice, however, the bond spread may also depend on many other factors that are not necessarily related to transparency, such as a country’s interest rate, stock market returns, inflation rates, and exchange rate movement. Suppose a country is following a predetermined devaluation path. In this situation, its bond spread will still increase even though the devaluation is pre-announced. Similarly, if the U.S. zero-coupon curve shifts upward, an emerging market’s bond spread can drop even though that emerging market has not implemented any reform to improve its transparency. Therefore, transparency is not directly related to bond spreads. Fund holdings and sovereign ratings all have a similar

\textsuperscript{15} Note that these theoretical models either look only at public information without considering private information or treat private information as exogenous/predetermined. In the next section, we will derive theoretical models for the equilibrium demand and supply of private information when public information is present.
problem: They can be greatly affected by macroeconomic variables that are not closely related to transparency.

This study argues that transparency is related to the gap between the expectation of an economic variable and its true value. If the exchange rate is depreciating and the international community has enough knowledge of the depreciation path, then the exchange rate policy is transparent. However, if the international community cannot predict the depreciation path, then the exchange rate policy is not transparent. If we can construct a variable that records the gap between investors’ perceived bond default rate and the actual bond default rate, this variable will better measure transparency’s effect than the bond spread proposed by Glennerster and Shin (2003).

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’ revenues, costs, and profits are affected by macroeconomic policies, more transparent policies can help stock analysts and investors forecast firms’ profits more accurately. If firms follow International Accounting Standards, then investors can glean more information from firms’ balance sheet, income, and cash flow statements. In this way, investors gain access to resources that allow them to accurately forecast firms’ futures. 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.

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

A few articles in the subfield of accounting have previously investigated how transparency affects forecasts. Lang and Lundholm (1996), for example, examine the relations between analysts' forecasts and the disclosure practices of firms. Focusing on U.S. firms, they find evidence that forecasts are more accurate and less dispersed for firms with more informative disclosure policies. Hope (2003) finds the same results by analyzing twenty-two countries. However, these studies focus on developed countries and
accounting rules, rather than on emerging markets and other transparency indicators such as SDDS implementation. Furthermore, their data sets cover the years before 1996, whereas the international community began to place heavy emphasis on transparency after the 1997 crisis.

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 and is essential to the performance of their task. 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. Lang and Lundholm (1996) and Hope (2003) find that more firm disclosure will increase analyst following. Hope (2003) further finds that as analyst following rises, forecast accuracy increases.

But neither Lang and Lundholm (1996) nor Hope (2003) provides explicit theoretical models of the impact of firm disclosure on analyst following. This paper will provide theoretical models to explain how greater access to public information (through mechanisms such as higher levels of firm disclosure) affects market participants’ incentives for private information (such as the demand of analyst following).

3. Theoretical Models

This section presents theoretical models 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. Basic Model

In this subsection, a model for the optimal production of private information is derived. The first supposition is that there is a single agent \( i \) who has the following payoff function:

\[ u_i(a_i, \theta) \equiv -(a_i - \theta)^2 \]

where \( \theta \) is the unobservable true value of the underlying state, and \( a_i \) is agent \( i \)'s belief of \( \theta \). The closer \( a_i \) is to \( \theta \), the better for agent \( i \). Agent \( i \) receives both free public information

\[ y = \theta + \eta \]

and collects private information

\[ x_i = \theta + \varepsilon_i \]

where \( \eta \) is normally distributed, independent of \( \theta \), with mean zero and precision \( \alpha \) (i.e., \( \frac{1}{\text{Var}[\eta]} \)). \( \varepsilon_i \) is normally distributed, independent of \( \theta \) and \( \eta \), with mean zero and precision \( \lambda \) (i.e., \( \frac{1}{\text{Var}[^\varepsilon_i]} \)). \( \alpha \) and \( \lambda \) are known to agent \( i \).

To maximize his expected payoff \( E[u_i(a_i, \theta)] \), agent \( i \) will choose \( a_i \) according to the following Bayesian updating rule\(^{16}\):

\[ \hat{a}_i = \frac{\alpha y + \lambda x_i}{\alpha + \lambda}. \]

The maximized \( E[u_i(a_i, \theta)] \), \( E[u_i(\hat{a}_i, \theta)] \), is

\[ E[u_i(\hat{a}_i, \theta)] = -E\left[ \left( \frac{\alpha y + \lambda x_i}{\alpha + \lambda} - \theta \right)^2 \right] \]

\[ = -\frac{1}{\alpha + \lambda}. \]

As one can see, when private information becomes more precise (i.e., when \( \lambda \) goes up), the expected payoff to agent \( i \) increases as well. However, there is cost associated with collecting private information. The cost is assumed to be a linear function of \( \lambda \):

\(^{16}\) Bayesian updating rules are explained on page 108 of Lyons (2001).
\[ C = \phi \lambda \]

where \( \phi \) is a positive constant. According to the cost function, as private information becomes more precise, the total production cost of obtaining private information increases. The agent \( i \) then needs to balance the benefit and cost of getting more precise private information. Specifically, he optimally chooses \( \hat{\lambda} \) by maximizing the following payoff, which includes both the benefit and the cost of private information:

\[
V(\hat{\lambda}) = E[u_i(\hat{a}_i, \theta)] - C = -\frac{1}{\alpha + \hat{\lambda}} - \phi \hat{\lambda}.
\]

The first order condition for maximizing \( V(\hat{\lambda}) \) implies that he will choose

\[
\hat{\lambda} = \frac{1}{\sqrt{\phi}} - \alpha.
\]

The equation for \( \hat{\lambda} \) shows that as public information becomes more precise (\( \alpha \) increases), the demand for private information accuracy drops. In particular, the crowding out effect between \( \alpha \) and \( \hat{\lambda} \) is one-to-one.

Evaluated at \( \hat{\lambda} \),

\[
E[u_i(\hat{a}_i, \theta)] = \frac{1}{\alpha + \hat{\lambda}} = \sqrt{\phi}
\]

which does not depend on \( \alpha \). Note that in this model, \( E[u_i(\hat{a}_i, \theta)] \) can be interpreted as how accurate agent \( i \)'s forecast of \( \theta \) is. Because \( E[u_i(\hat{a}_i, \theta)] \) does not depend on \( \alpha \), the precision of public information will not affect agent \( i \)'s forecast accuracy for \( \theta \).

In this basic model, the one-to-one crowding out between \( \alpha \) and \( \hat{\lambda} \) suggests that the crowding out effect will be the same no matter how large \( \alpha \) is. That is to say, \( \frac{\partial \hat{\lambda}}{\partial \alpha} = -1 \).

Empirical results of this study, however, find that the crowding out effect is larger when \( \alpha \) is smaller.\(^{17}\) That is to say, \( \frac{\partial^2 \hat{\lambda}}{\partial^2 \alpha} > 0 \). Next, different function forms for the cost of producing private information are examined. With the information cost function

\(^{17}\) This study finds that the crowding out effect is bigger in developing countries than in developed countries. Developed countries tend to have higher public transparency (higher \( \alpha \)) than developing countries. This suggests that the crowding out effect decreases as \( \alpha \) increases.
\[ C = \phi \lambda^s, \] when \( s > 1 \), the crowding decreases as \( \alpha \) goes up \( \left( \frac{\partial \hat{\lambda}}{\partial \alpha} < 0, \frac{\partial^2 \hat{\lambda}}{\partial^2 \alpha} > 0 \right) \), and the net effect of \( \alpha \) on information accuracy is positive \( \left( \frac{\partial E[u_i(\hat{\lambda}, \theta)]}{\partial \alpha} > 0 \right) \). However, when \( s < 1 \), the crowding increases as \( \alpha \) goes up \( \left( \frac{\partial \hat{\lambda}}{\partial \alpha} < 0, \frac{\partial^2 \hat{\lambda}}{\partial^2 \alpha} < 0 \right) \), and the net effect of \( \alpha \) on information accuracy is negative \( \left( \frac{\partial E[u_i(\hat{\lambda}, \theta)]}{\partial \alpha} < 0 \right) \).

3.2. **Model with Strategic Interaction**

The basic model outlined above studies a single representative agent \( i \). What if there is more than one agent in the economy? Can we say anything about the dispersion of beliefs across multiple agents? To address this question, we need to move from a single-agent model to a model that includes a group of agents. Previous work has placed particular emphasis on the herding and peer effects among investors.\(^{18}\) 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 for this multiple-agent model is the work of Morris and Shin (2002), who develop a strategic interaction model to study the social values of public information. Morris and Shin (2002) provide a useful model for the following three 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 includes both public and private information. Third, 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 they 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. Second, how the crowding out between public and private information affects information dispersion is examined. When public information is not

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\(^{18}\) Previous works on herding and information cascades include Banerjee (1992), Bikhchandani, Hirshleifer and Welch (1992) and Cao and Hirshleifer (2000).
precise, I find that the crowding out effect will shrink the influence of public information on information dispersion. Moreover, owing to strategic interaction among agents, the net influence of public information precision on information accuracy can be negative even when the information cost is linear.

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:

\[
u_i(a_i, \theta) = -(1-r)(a_i - \theta)^2 - r(L_i - \bar{L})
\]

where \(r\) is a constant, with \(0 < r < 1\), and

\[
L_i = \int_0^1 (a_j - a_i)^2 \, dj, \quad \bar{L} = \int_0^1 L_j \, dj
\]

The payoff function for individual \(i\) has two components. The first is a standard quadratic payoff in the distance between his action \(a_i\) and the unobservable underlying state \(\theta\). The second component is the “beauty contest” term, which provides the motivation for herding. \(L_i\) is increasing in the average distance between agent \(i\)’s action and the action profile of the entire population. The parameter \(r\) gives the weight on the second-guessing incentive.

Agent \(i\) will receive both public information \(y = \theta + \eta\), and private information \(x_i = \theta + \epsilon_i\). \(\eta\) is normally distributed, independent of \(\theta\), with mean zero and precision \(\alpha\). \(\epsilon_i\) is normally distributed, independent of \(\theta\), \(\eta\) and \(\epsilon_j\), with mean zero and precision \(\beta\). Morris and Shin (2002) argue that when \(\beta\) is in a certain range, the social welfare can decrease as \(\alpha\) increases, where the social welfare is

\[
W = -\int_0^1 (a_i - \theta)^2 \, di
\]

In this study, I define information accuracy as \(E[(\hat{a}_i - \theta)^2]\), which is the expected value of the social welfare \(W\). Information dispersion is defined as

\[
Dispersion \equiv (E[\int_0^1 (a_i - \bar{a})^2 \, dj])^{0.5}
\]

where \(\bar{a}\) is the average of \(a_i\). Appendix I derives
\[
\text{Dispersion} = \frac{(1-r)\sqrt{\beta}}{\beta(1-r) + \alpha}
\]

which suggests that as public information precision \( \alpha \) increases, information dispersion will decrease.

However, Morris and Shin (2002) treat \( \beta \) as exogenous. I will extend their model by endogenizing the production of private information. Moreover, the production cost function for private information is assumed to be \( C = \phi\beta \).

Appendix I shows that increased public information precision will crowd out the incentive for acquiring private information. The optimal private information precision \( \hat{\beta} \) in the equilibrium is

\[
\hat{\beta} = \frac{1}{\sqrt{\phi}} - \frac{\alpha}{1-r}.
\]

Therefore, unless \( r = 0 \), the crowding out is greater than one-to-one.

In the equilibrium, agents’ information accuracy is

\[
E[(\hat{a}_i - \theta)^2] = \sqrt{\phi} - \frac{\alpha\phi}{(1-r)^2}.
\]

In this way, higher public information precision will actually decrease information accuracy.

Similarly, in the equilibrium, information dispersion becomes

\[
\text{Dispersion} = \sqrt{\phi^{0.5} - \frac{\alpha\phi}{1-r}}
\]

which implies that increased precision of public information will decrease information dispersion. When \( \alpha < \frac{1-r}{2\sqrt{\phi}} \), the effect of \( \alpha \) on dispersion will be smaller than if no crowding out existed. However, when \( \alpha > \frac{1-r}{2\sqrt{\phi}} \), the effect of \( \alpha \) on dispersion will be bigger than if no crowding out were present.

3.3. Testable Implications

To test the theoretical results derived above, the following three empirical models are proposed. The first model is
\[ E[(a_i - \theta)^2] = \pi_{10} + \pi_{11}\alpha + \pi_{12}\beta_1(\alpha) + \nu_1 \]

where \( E[(a_i - \theta)^2] \) is information accuracy, and \( \nu_1 \) is a disturbance term. The basic theoretical model suggests that \( E[(a_i - \theta)^2] \) will not depend on the precision of public information when the cost function is linear. Therefore, the first null hypothesis is

\[ \pi_{11} + \pi_{12} \frac{\partial \beta_1}{\partial \alpha} = 0. \]

The second model is

\[
(E[\int_0^t (a_i - \bar{a})^2 \, d_i])^{0.5} = \pi_{20} + \pi_{21}\alpha + \pi_{22}\beta_1(\alpha) + \nu_2
\]

where \((E[\int_0^t (a_i - \bar{a})^2 \, d_i])^{0.5}\) is information dispersion, and \(\nu_2\) is a disturbance term. The herding model suggests that \(\pi_{22}\) can be either positive, negative, or zero, depending on whether \(\alpha > \frac{1-r}{2\sqrt{\phi}}\) or \(\alpha < \frac{1-r}{2\sqrt{\phi}}\). The second null hypothesis is then \(\pi_{22} = 0\).

The third empirical model is

\[ \beta_1 = \pi_{30} + \pi_{31}\alpha + \nu_3 \]

where \(\nu_3\) is a disturbance term. Both the basic model and the herding model suggest that the precision of private information (\(\beta_1\)) will be smaller when \(\alpha\) is larger. The third null hypothesis is \(\pi_{31} < 0\). The basic model also suggests that with different cost function forms, the crowding out effect can be smaller/the same/bigger as \(\alpha\) becomes larger. To test this point, the fourth null hypothesis will be \(\frac{\partial \pi_{31}}{\partial \alpha} = 0\).

I now test these four hypotheses by examining data on the earnings forecasts of stock market analysts. I use analyst forecasts for the following reasons. First, international standards and codes 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 local firms implement 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 policy and information about the public sector finances. To forecast a firm’s earnings (profits), it is necessary to understand the economic situation of the country in which it operates. If the country will be in recession, then the firm’s sales are likely to decline, reducing its profits. If the government plans to depreciate the currency, then the profits for exporting firms are likely to go up, while the profits for importing firms are likely to go down.

Third, and critically for present purposes, the stock analyst data base 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.

4. Data and Variables

This section describes my data sources and defines the dependent and explanatory variables.

4.1. Data Description

Stock analyst forecasting data were obtained from the Institutional Brokers Estimates System (IBES) database. The IBES 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 code, analyst code, estimate date, estimate value, actual value report date, actual reported value, currency, industry name, 5-year growth of the measure, 5-year stability of the measure, stock price, and shares outstanding.

The accounting research mentioned earlier, such as Lang and Lundholm (1996) and Hope (2003), has also relied on IBES. 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.

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 of the 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 a group of analysts who agree to provide their estimates in return for free use of IBES products or data. 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. When these are satisfied, a country is said to have fulfilled the requirements of the SDDS.

The IAS adoption variable is constructed from the 2000 and 2001 GAAP surveys, which benchmarked national accounting rules against IAS. These surveys asked large accounting firms in more than 60 countries to benchmark their local written requirements against approximately 80 accounting measures, focusing on standards (both IAS and national) in force for the financial reporting period ending 31 December 2000 or 2001. The surveys identified, for the selected accounting measures, instances in which a
country would not allow or would not require IAS treatment. The 2001 survey also identified progress that had been made in achieving convergence in the years 2000 and 2001, as well as possible progress in 2002. I also referred to www.iasplus.com to identify when a country had adopted certain IAS rules, since this website traces some countries as far back as 1997.

In what follows I examine analysts’ forecasting data for stocks in 60 countries between 1990 and 2002. Stocks from Canada, Japan, the United Kingdom, and the United States are not included, because these four markets have far more stocks than other markets. If included, these markets might dominate the estimates, making it difficult to estimate the effects of transparency on smaller economies. Markets in which fewer than 10 stocks were covered, typically very small countries such as Slovenia and 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 1998 (in the case of a three-year forecasting horizon), 1999 (a two-year forecasting horizon), and 2000 (a one-year forecasting horizon). In the empirical works that follows I focus on the one-year-ahead forecasts. 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 analysts’ forecasts for a stock in a given 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 forecast dispersion.

Forecast error is defined in the following manner:

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19 Another possibility is to randomly select some stocks from these three countries. However, IBES tends to cover big rather than small stocks, so caution is required in setting the selection criteria.
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.\footnote{Note that the forecasting error so far is defined as a positive number.} 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.\footnote{Note that there can be multiple estimates and thus residuals for each stock per accounting year.}

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

\[ \text{For} \quad \text{the} \quad \text{accounting} \quad \text{year} \quad \text{ending} \quad \text{in} \quad \text{December,} \quad \text{some} \quad \text{analysts} \quad \text{provide} \quad \text{forecasts} \quad \text{in} \quad \text{March,} \quad \text{and} \quad \text{some} \quad \text{provide} \quad \text{these} \quad \text{in} \quad \text{November.} \quad \text{Intuitively,} \quad \text{the} \quad \text{estimates} \quad \text{offered} \quad \text{in} \quad \text{November} \quad \text{will} \quad \text{have} \quad \text{smaller} \quad \text{forecast} \quad \text{errors.} \quad \text{To} \quad \text{control} \quad \text{for} \quad \text{this} \quad \text{forecasting-time} \quad \text{effect,} \quad \text{I} \quad \text{regress} \quad \text{the} \quad \text{forecast} \quad \text{error} \quad \text{on} \quad \text{the} \quad \text{time} \quad \text{difference} \quad \text{from} \quad \text{the} \quad \text{forecasting} \quad \text{month} \quad \text{to} \quad \text{the} \quad \text{end} \quad \text{of} \quad \text{the} \quad \text{accounting} \quad \text{year.}^20 \text{I} \quad \text{do} \quad \text{this} \quad \text{using} \quad \text{a} \quad \text{pooled} \quad \text{regression} \quad \text{for} \quad \text{all} \quad \text{stocks} \quad \text{over} \quad \text{the} \quad \text{whole} \quad \text{sample} \quad \text{period.} \quad \text{For} \quad \text{each} \quad \text{stock} \quad \text{per} \quad \text{accounting} \quad \text{year,} \quad \text{the} \quad \text{mean} \quad \text{of} \quad \text{the} \quad \text{residuals} \quad \text{from} \quad \text{the} \quad \text{above} \quad \text{regression} \quad \text{is} \quad \text{calculated} \quad \text{as} \quad \text{the} \quad \text{average} \quad \text{forecast} \quad \text{error.}^21

\subsection*{4.2.2. Transparency variables}

- IAS adoption

I base my measure of IAS adoption on accounting rules that are adopted by at least \(20\%\) and no more than of \(80\%\) of the countries in the sample.\footnote{These accounting rules are IAS1, IAS2, IAS7, IAS8, IAS12, IAS14, IAS16, IAS17, IAS18, IAS21, IAS24, IAS27, IAS28, IAS33, and IAS35.} If all countries (or nearly all countries) are adopting or not adopting a certain accounting rule, then there is insufficient variation across countries to analyze its effects; this is why I disregard rules adopted by fewer than \(20\) per cent or more than \(80\) per cent of sample countries. I first construct a dummy variable for each accounting rule, which equals 1 when that rule is adopted. The square root of the sum over these adoption dummies is then calculated to construct a single composite index of IAS adoption. The IAS adoption data cover the period from 1997 through 2002. Before 1997, I do not have information on when a country started using a certain IAS rule. Although some IAS rules were developed in the early 1990s, but the GAAP surveys and IASPLUS website together cover only the period 1997-2002. To give a flavor of the resulting composite index, Table 1 presents the values for 2001.

- SDDS fulfillment

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 very 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 very similar.

4.2.3. **Control variables**

- **Industry dummies.** There are eleven industries, e.g., finance and consumer products.

- **Firm size.** Firm size is defined as the log value of the market capitalization, which is the stock price (in U.S. dollar terms) multiplied by the shares outstanding. Since the stock price varies over the sample period, median firm size over the sample period 1990 to 2003 is used. In this way, the firm size variable will be the same over the sample period for every stock.

- **Earnings surprise.** This is the absolute value of the percentage change in the actual earnings per share (in dollar terms). The formula for the earnings surprise is

\[
Earnings\ surprise(t) = \left| \frac{Actual(t) - Actual(t-1)}{Actual(t)} \right|
\]

The earnings surprise is included to control for the fact that when earnings surprise is high, forecast error is also likely to be high. The definition of the earnings surprise here is different from the traditional definition, where this variable is defined as the unexpected shock to a variable instead of the change of
that variable over time. However, the definition here is consistent with the literature on analyst forecast errors. Subsequently, in the section on sensitivity analysis, I drop the earnings-surprise variable and show that the results are little changed.

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

- **Time dummies.** Year dummies are used to control for the extent to which global stock markets are doing well or badly in a given year.

- **Macroeconomic variables,** such as GDP per capita, inflation rate, GDP growth rate, and the number of listed domestic stocks in a country. In the estimates that follow I use one-year lags of these variables.

5. **Empirical Models and Results**

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

\[
\text{Mean Forecast Error}_{ijt} = \omega_{11} + \omega_{12}\text{Transparency}_{jt} + \omega_{13}\text{Size}_{jt} + \omega_{14}\text{Industry}_{jt} + \omega_{15}\text{Surprise}_{jt} + \omega_{16}\text{Loss}_{jt-1} + \omega_{17}\text{AnalystNumber}_{jt} + \omega_{18}\text{Time}_{jt} + \omega_{19}\text{Macro}_{jt-1} + \epsilon_{1,ijt}
\]

where \(i, j,\) and \(t\) stands for stock \(i\) in country \(j\) at time \(t\). Moulton (1990) argues that, when estimating the effects of aggregate variables (such as IAS adoption) on a micro dataset, disturbance terms \(\epsilon_{1,ijt}\) may not be independent over the group where the value of the aggregate variable is defined as the same. Therefore, robust standard errors, with clustering considered, will be estimated to control for the possible interdependence of \(\epsilon_{1,ijt}\) across \(j\).

The second model studies the dispersion of analyst forecasts:

\[
\text{Forecast Dispersion}_{ijt} = \omega_{21} + \omega_{22}\text{Transparency}_{jt} + \omega_{23}\text{Size}_{jt} + \omega_{24}\text{Industry}_{jt} + \omega_{25}\text{Surprise}_{jt} + \omega_{26}\text{Loss}_{jt-1} + \omega_{27}\text{AnalystNumber}_{jt} + \omega_{28}\text{Time}_{jt} + \omega_{29}\text{Macro}_{jt-1} + \epsilon_{2,ijt}
\]

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

\[
\text{Analyst Number}_{ijt} = \omega_{31} + \omega_{32}\text{Transparency}_{jt} + \omega_{33}\text{Size}_{jt} + \omega_{34}\text{Industry}_{jt} + \omega_{35}\text{Loss}_{jt-1} + \omega_{36}\text{Time}_{jt} + \omega_{37}\text{Macro}_{jt-1} + \epsilon_{3,ijt}
\]
Analyst number is a proxy for market participants’ investments in acquiring private information ($\beta_i$ in the theoretical model), while Transparency is the proxy for the precision of public information ($\alpha$ in the theoretical model). These three models are estimated separately for IAS adoption and SDDS implementation. The empirical results are as follows.

5.1. IAS Adoption

Benchmark results for IAS adoption are in Table 2, 3 and 4. Table 2 records the direct and net effects of IAS adoption on forecast error in developing countries. Table 3 records the effect of IAS adoption on analyst following in developing countries. The sample is then expanded to include developed countries to study how the crowding out effect changes with a country’s developing level (Table 4). Since IAS adoption does not change over time for most countries between 1997 and 2002, the panel regression estimates reported in these three tables are equivalent to pooled cross section analysis.

The results, in Table 2, show that IAS adoption directly reduces forecast error. The estimated value of the direct effect, at -.28, is significantly different from zero at the 92% confidence level (first column). This is consistent with the view that timely and comprehensive accounting reports give analysts more accurate information on a firm’s operation. The median value of forecast error for each stock is 0.7. Therefore, if the composite IAS adoption index goes up by one, the forecast error will drop by 40%.

Another result derived from Table 2 is that higher analyst following will decrease forecast error. The coefficient on analyst number (square root) is -0.23, different from 0 at a 0.2% significance level. As the number of analysts (square root) increases by 1, the forecast error will drop by 0.23, which is 33% of the original forecast 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

23 Standard errors here are adjusted according to Moulton (1990).
24 For the developing countries, the composite index of IAS adoption is 1.73 at the 25% quantile and 3.3 at the 75% quantile.
diminishing marginal effect of additional analysts in Table 2. Using the number of analysts instead of the square root yields similar results, though the former is not as significant as the latter.

However, the net influence of IAS adoption on forecast accuracy is insignificant. The net effect is an aggregate of both the direct effect of IAS adoption (-0.28, as above), and the indirect effect owing to the decreasing analyst number after IAS adoption. The second column of Table 2 records the net effect of IAS adoption. There, analyst following is excluded from the explanatory variable set. The coefficient of IAS will be a measure of its net effect, which is –0.23 and different from zero at an 86% confidence level. Thus, the net effect is only 80% of the direct effect, owing to the 20% opposite indirect effect.

The indirect effect is presented in Table 3. The results there show that IAS adoption is associated with a decreased analyst following. As the IAS adoption index increases by one, 20% of the analysts will leave the forecasting market. For developing countries, the mean value of the analyst number is 4. In this instance, a 20% decrease means that there will be one less analyst per stock. Since the number of analysts is an ordered discrete number, a Probit model is also estimated: The result is the same qualitatively, and the significance levels of coefficients are comparable (as in the second column of Table 3).

The indirect effect of IAS adoption, then, is the product of the effect of analyst number on forecast error (-0.23 in Table 2) and the effect of IAS adoption on analyst number (-0.19 in Table 3). The indirect effect, measured in this way, is similar to that discussed in the previous paragraph.

The results in Table 3 contrast with Lang and Lundholm (1996) and Hope (2003), who find that more disclosure by firms will increase the analyst following. This difference may be explained by the fact that Table 3 reports results for emerging markets, while Lang and Lundholm (1996) and Hope (2003) look at developed countries. Moreover, Lang and Lundholm (1996) and Hope (2003) use firm level’s disclosure index instead of country level’s disclosure index. And their data covers years 1991-1996 for a small number of firms. Since they focus on developed countries, the approach here
checked how IAS adoption affects the number of analysts by limiting the samples to OECD countries.\textsuperscript{25} For 17 OECD countries, IAS adoption has no significant effect.

Moreover, as a country becomes more developed, the effect of IAS adoption on analyst following decreases. In Table 4, the empirical model is estimated as in Table 3, except that developed countries are added. The coefficient of IAS adoption is still significantly negative at -1, but the coefficient of IAS adoption interacted with GDP per capita is significantly positive at 0.09. In the sample period 1997 to 2002, the lowest GDP per capita is 6, and the highest is 10.88, with the mean at 9.8. This suggests that the crowding out effect of IAS adoption is small for developed countries.

The different results for OECD and non-OECD countries are consistent with one implication in the earlier basic theoretical model: In countries where the public signal is more precise (i.e., higher $\alpha$), the marginal crowding-out effect on private information precision ($\hat{\lambda}$) will be smaller if the information function is convex ($S>1$).\textsuperscript{26} It has been the consensus that OECD countries have more precise public signals compared with non-OECD countries. Therefore, the crowding out effect (i.e, the decrease of analyst following) will be much smaller in OECD countries.

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. Consensus 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

\textsuperscript{25} The Czech Republic, Greece, Hungary, Korea, Mexico, Poland, Slovak Republic and Turkey, are regarded as belonging to Non-OECD countries, because they are not as developed as the remaining OECD countries. There are, applying this standard, 30 Non-OECD countries and 17 OECD countries, excluding Canada, Japan, the United Kingdom, and the United States.

\textsuperscript{26} Note that the first derivative of $\hat{\lambda}$ with respect to $\alpha$ is negative, but the second derivative is positive.
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.
Table 5 presents the effect of IAS adoption on information dispersion. The direct effect of IAS is –0.058, different from zero at the 3% significance level (first column). The net effect of IAS is –0.047, different from zero at the 6% significance level (second column). The indirect effect is thus around 20% of the direct effect. More analysts per stock will decrease forecast dispersion (first column), which is consistent with the theoretical argument that when \( \alpha < \frac{1-r}{2\sqrt{\phi}} \), the effect of \( \alpha \) on dispersion will become smaller after the crowding out.

5.2. SDDS Implementation

The benchmark results for the SDDS are in Table 6 though 9. Table 6 presents the direct and net effects of the SDDS on the forecast error in developing countries, while Table 7 shows the effect of the SDDS on analyst following in developing countries. The sample is then expanded to include developed countries in order to study how the crowding out effect changes with a country’s developing level (Table 8). Although IAS adoption does not change much across time in the sample period 1997 to 2002, SDDS implementation does change over time.\(^\text{27}\) 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 1991-2002. 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 -0.17, is significantly different from zero at the 96% 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 25%.

\(^\text{27}\) The earliest implementation date is Feb 19, 1999, by the U.S. Some countries, such as Russia, have not yet fulfilled the requirement.
The fixed effects model (Table 6) confirms the cross-section result in Table 2 that higher analyst following reduces the forecast error. The coefficient on the square root of the number of analysts is -0.16 and different from zero at the 0.2% significance level. When the analyst number (square root) increases by 1, in other words, the forecast error drop by 0.16, which is 22% of the initial error.

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 (-0.17 as above), and the indirect effect owing to the drop of analyst number after fulfillment. The net effect of the SDDS is presented in the second column of Table 6. 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 –0.14 and different from zero only at the 91% confidence level. Thus, the net effect is only 80% of the direct effect, owing to the indirect effect working in the opposite direction.

Table 7 presents additional analysis of the indirect effect. The results show that the SDDS is associated with a reduced analyst following. 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 (-0.16 in Table 6) and the effect of the SDDS on analyst number (-0.19 in Table 7). The indirect effect measured in this way is similar to that in the previous paragraph.

It also appears that the impact of the SDDS on the number of analysts weakens as countries become more developed. The results in Table 8 are similar to those in Table 7 except that developed countries are added. The coefficient on the SDDS is still significantly negative, at-0.9, but the coefficient of the SDDS interacted with GDP per capita is significantly positive at 0.08. This suggests that the crowding out effect is much smaller for developed countries.

Table 9 analyzes the impact of the SDDS on information dispersion. Its direct effect is -0.0551, significantly different form zero at four percent level (first column). The net effect of the SDDS is -0.0374 and different form zero at 17% significance level (second
column). The indirect effect thus is around 40% of the direct effect. More analysts per stock will decrease forecast dispersion (first column), which is consistent with the theoretical argument that when $\alpha < \frac{1-r}{2\sqrt{\phi}}$, the effect of $\alpha$ on dispersion will become smaller after the crowding out.

5.3. Control Variables

Most of the control variables enter as expected. The coefficients on the ten industry dummies are not significantly different from zero in the regression for either analyst forecast error or analyst number; consequently they are not reported in the tables. Table 2 and 6 show 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 and 7). 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.

The signs of the macroeconomic controls are also intuitive. Inflation is negatively related to forecast accuracy and positively associated with analyst following (Table 2, 3, 6, and 7). The GDP growth rate is also negatively related to forecast accuracy and positively associated with analyst following (Table 2, 3, 6, and 7). The number of domestic listed stocks is positively related to forecast accuracy (Table 2). This result suggests that as the stock market becomes larger and more important, analyst forecast error drops. At the same time, the number of domestic listed stocks is negatively related to analyst number (Table 3 and 7). A possible reason is that stocks are competing for analysts. If the total supply of analysts is relatively inelastic in the short-run, then more competition among stocks implies fewer analysts per stock.
5.4. Robustness Checks

I also looked at whether adding other characteristics of firms affects the impact on earnings forecasts. 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 30% for IAS adoption and by 50% for SDDS implementation. Nevertheless, the key results on the effects of IAS and the SDDS are not altered significantly.

The earnings surprise is included in earlier estimates of forecast accuracy to allow for cases in which firms have big shocks that could not be reasonably anticipated by analysts. Inclusion of this variable is presumably controversy (for not all shocks are big shocks, and it is not clear where to draw the line). But excluding this variable does not change the key results for IAS adoption. The direct effect of IAS adoption on the forecast error is still significantly negative, and the indirect effect remains at 20% of the direct effect. The results do change somewhat in this case for SDDS implementation. When the earnings surprise is excluded, the indirect effect rises from 0.03 to 0.04, while the direct effect falls from 0.17 to 0.04. In this case the indirect effect fully offsets the direct effect; and the estimated value of the net effect is 0.006 (instead of -0.14 as previously), which is not different from zero statistically or economically.

In studying the IAS effect, cross-section analysis is used because many countries do not have variations in IAS adoption over the sample period 1997-2002. For the SDDS, this study has used panel estimation with fixed effects. I now estimate the effects of the SDDS by using the cross-section analysis. If the cross-section analysis is comparable to the panel analysis for the SDDS, then we can have a reasonable belief in the cross-section analysis for IAS adoption. The results show that the cross-section analysis and panel-data analysis are comparable. In terms of SDDS’s direct effect on forecast error, panel analysis produces an effect of -0.17, while cross-section analysis produces a value of -0.16. In terms of the SDDS’s influence on the number of analysts, the panel method produces a value as -0.18, while cross-section analysis produces one of -0.20.
6. Conclusion

This paper has analyzed the impact of transparency standards on the information environment. It has provided a sequence of models useful for analyzing the potential for private information to be crowded out by public disclosure. The representative-agent and heterogeneous-agent models both suggest that transparency standards which improve agents’ access to public information may at the same time weaken market incentives to make costly investments 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 IAS adoption and SDDS implementation. I find that the direct effects on forecast error and dispersion of both IAS adoption and 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 transparency standards ranges from weak to the nonexistent. This crowding out effect is larger in developing than developed countries, which is worrisome insofar as recent transparency-related initiatives have been targeted at developing countries in particular.

These findings do not suggest that the transparency 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.
References


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<td>Turkey</td>
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Sources: GAAP surveys (2000 and 2001) and IAS plus website.
Table 2: Effect of IAS Adoption on Forecast Error  
(Developing countries)

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<td>-0.226</td>
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<td>(0.072)</td>
<td>(0.153)</td>
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<tr>
<td>IAS adoption</td>
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<td>-0.226</td>
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<tr>
<td>(0.161)</td>
<td>(0.153)</td>
<td></td>
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<tr>
<td></td>
<td>(0.030)</td>
<td>(0.030)</td>
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<tr>
<td>Firm size</td>
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<td></td>
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<td>(0.027)</td>
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<tr>
<td></td>
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<td>-0.007</td>
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<tr>
<td></td>
<td>(0.040)</td>
<td>(0.042)</td>
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<tr>
<td>Number of domestic stocks</td>
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<td>-0.010</td>
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<tr>
<td>(square root)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>GDP growth rate</td>
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</tr>
<tr>
<td></td>
<td>(4.000)</td>
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</tr>
<tr>
<td>Stock market capitalization over GDP</td>
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<td>-0.0001</td>
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<tr>
<td></td>
<td>(0.0006)</td>
<td>(0.0006)</td>
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<tr>
<td>GDP per capita</td>
<td>0.124</td>
<td>0.125</td>
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<tr>
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<tr>
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<tr>
<td>R-squared</td>
<td>0.38</td>
<td>0.37</td>
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Note: Standard errors in parentheses. Yearly dummies are included in estimation, though the coefficients are not reported here. Coefficients significantly different from zero at the .05 value are in bold.
Table 3: Impact of IAS Adoption on Analyst Number (developing countries)

<table>
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<tr>
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<tr>
<td>IAS adoption</td>
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<tr>
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<td>(0.038)</td>
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<td>0.472</td>
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<tr>
<td>Loss</td>
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<td>-0.349</td>
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<tr>
<td></td>
<td>(0.035)</td>
<td>(0.042)</td>
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<tr>
<td>Inflation rate</td>
<td>0.055</td>
<td>0.071</td>
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<tr>
<td></td>
<td>(0.021)</td>
<td>(0.023)</td>
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<tr>
<td>Number of domestic stocks (square root)</td>
<td>-0.005</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
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<tr>
<td>GDP growth rate</td>
<td>0.800</td>
<td>0.615</td>
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<tr>
<td></td>
<td>(1.05)</td>
<td>(1.218)</td>
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<tr>
<td>Stock market capitalization over GDP</td>
<td>0.001</td>
<td>0.001</td>
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<tr>
<td></td>
<td>(0.0004)</td>
<td>(0.0004)</td>
</tr>
<tr>
<td>GDP per capita</td>
<td>0.007</td>
<td>0.021</td>
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<tr>
<td></td>
<td>(0.037)</td>
<td>(0.042)</td>
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<tr>
<td>Constant</td>
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<tr>
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<td>R-squared</td>
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</table>

Note: Standard errors in parentheses. Yearly dummies are included in estimation, though the coefficients are not reported here. Coefficients significantly different from zero at the .05 value are in bold.
<table>
<thead>
<tr>
<th>Variable</th>
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<th>Standard Error</th>
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<tr>
<td>IAS adoption</td>
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<td>(0.266)</td>
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<tr>
<td>IAS interacted with GDP per capita</td>
<td>0.094</td>
<td>(0.029)</td>
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<tr>
<td>Firm size</td>
<td>0.522</td>
<td>(0.018)</td>
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<tr>
<td>Loss</td>
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<td>(0.027)</td>
</tr>
<tr>
<td>Inflation rate</td>
<td>0.050</td>
<td>(0.022)</td>
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<tr>
<td>Number of domestic stocks (square root)</td>
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<tr>
<td>GDP growth rate</td>
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<td>Stock market capitalization over GDP</td>
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<td>(0.0003)</td>
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<td>GDP per capita</td>
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<td>R-squared</td>
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Note: Standard errors in parentheses. Yearly dummies are included in estimation, though the coefficients are not reported here. Coefficients significantly different from zero at the .05 value are in bold.
### Table 5: Impact of IAS Adoption on Forecast Dispersion (Developing countries)

<table>
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<tr>
<td>Number of analysts (square root)</td>
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<td>-0.047</td>
</tr>
<tr>
<td>IAS adoption</td>
<td>-0.058</td>
<td>-0.047</td>
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<tr>
<td>Firm size</td>
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<td>-0.036</td>
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<tr>
<td>Loss</td>
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<tr>
<td>Inflation rate</td>
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<tr>
<td>Number of domestic stocks (square root)</td>
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<td>-0.005</td>
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<tr>
<td>GDP growth rate</td>
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<td>Stock market capitalization over GDP</td>
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<tr>
<td>GDP per capita</td>
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<td>R-squared</td>
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Note: Standard errors in parentheses. Yearly dummies are included in estimation, though the coefficients are not reported here. Coefficients significantly different from zero at the .05 value are in bold.
Table 6: Impact of the SDDS on Forecast Error
(Developing countries)

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<td>Number of analysts (Square root)</td>
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<td>SDDS implementation</td>
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<td>Earnings surprise</td>
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<td>Loss</td>
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<td>Inflation rate</td>
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<td>Number of domestic stocks (square root)</td>
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<td>GDP growth rate</td>
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Note: Standard errors in parentheses. Yearly dummies are included in estimation, though the coefficients are not reported here. Coefficients significantly different from zero at the .05 value are in bold.
### Table 7: Impact of the SDDS on Analyst Number (Developing countries)

<table>
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<td>(0.015)</td>
</tr>
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<td>Inflation rate</td>
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<td>(0.0006)</td>
</tr>
<tr>
<td>Number of domestic stocks (square root)</td>
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<td>(0.002)</td>
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<tr>
<td>GDP growth rate</td>
<td>0.921</td>
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<td>Stock market capitalization over GDP</td>
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<td>(0.0001)</td>
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<td>Constant</td>
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<td>(0.052)</td>
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</table>

Number of obs: 29387

Note: Standard errors in parentheses. Yearly dummies are included in estimation, though the coefficients are not reported here. Coefficients significantly different from zero at the .05 value are in bold.
Table 8: Impact of the SDDS on Analyst Number  
(All countries)

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<td>SDDS implementation</td>
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<td>SDDS interacted with GDP per capita</td>
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<td>(0.009)</td>
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<td>Loss</td>
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<td>(0.010)</td>
</tr>
<tr>
<td>Inflation rate</td>
<td>0.002</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Number of domestic stocks (square root)</td>
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<td>(0.001)</td>
</tr>
<tr>
<td>GDP growth rate</td>
<td>1.054</td>
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<td>Stock market capitalization over GDP</td>
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</table>

Note: Standard errors in parentheses. Yearly dummies are included in estimation, though the coefficients are not reported here. Coefficients significantly different from zero at the .05 value are in bold.
Table 9: Effect of the SDDS on Forecast Dispersion  
(Developing countries)

<table>
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<td>Number of analysts</td>
<td>-0.111</td>
<td>0.010</td>
</tr>
<tr>
<td>(Square root)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SDDS implementation</td>
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<td>0.027</td>
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<tr>
<td></td>
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<tr>
<td></td>
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</tr>
<tr>
<td>Number of domestic stocks</td>
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<td>0.0025</td>
</tr>
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<td>GDP growth rate</td>
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<td>Observations</td>
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Note: Standard errors in parentheses. Yearly dummies are included in estimation, though the coefficients are not reported here. Coefficients significantly different from zero at the .05 value are in bold.
Appendix I

In this appendix, 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 in the equilibrium.


Morris and Shin (2002) assume that 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

\[
 u_i(a_i, \theta) = -(1 - r)(a_i - \theta)^2 - r(L_i - \bar{L})
\]

where \(r\) is a constant, with \(0 < r < 1\); and

\[
 L_i \equiv \int_0^1 (a_j - a_i)^2 \, dj \\
 \bar{L} \equiv \int_0^1 L_j \, dj.
\]

The payoff function for individual \(i\) has two components. The first is a standard quadratic payoff in the distance between his action \(a_i\) and the unobservable underlying state \(\theta\). The second component is the “beauty contest” term. \(L_i\) is increasing in the average distance between agent \(i\)’s action and the action profile of the entire population. The parameter \(r\) gives the weight on the second-guessing incentive.

Agent \(i\) observes both public signal

\[
y = \theta + \eta
\]

and private signal

\[
x_i = \theta + \epsilon_i.
\]

\(\eta\) is normally distributed, independent of \(\theta\), with mean zero and precision \(\alpha\), where

\[
\alpha \equiv \frac{1}{\text{Var}[\eta]}.
\]

\(\epsilon_i\) is normally distributed with mean zero and precision \(\beta\), where

\[
\beta \equiv \frac{1}{\text{Var}[\epsilon_i]}.
\]
\( \varepsilon_i \) is independent of \( \theta, \eta, \) and \( \varepsilon_j \). Agent \( i \) cannot observe other agents’ private signals. \( \alpha \) and \( \beta \) are known to all agents. Moreover, all agents have the same \( \alpha \) and \( \beta \).

The first order condition for payoff-maximizing suggests the optimal action for agent \( i, \hat{a}_i, \) is

\[
\hat{a}_i = (1-r)E_i[\theta] + rE_i[\bar{a}]
\]

where \( \bar{a} = \int_0^1 \hat{a}_jdj \). \( E_i[\cdot] \) is the expectation operator for agent \( i \), conditional on \( x_i \) and \( y \).

For all values of \( \alpha \) and \( \beta \), the unique equilibrium action is

\[
\hat{a}_j = kx_j + (1-k)y, \quad \text{for all } j
\]

where

\[
k = \frac{\beta(1-r)}{\beta(1-r) + \alpha}.
\]

Therefore, in the equilibrium,

\[
E_i[\bar{a}] = kE_i[\theta] + (1-k)y
\]

where

\[
E_i[\theta] = \frac{\alpha y + \beta x_i}{\alpha + \beta}.
\]

Moreover, Morris and Shin (2002) define the social welfare \( W \) as

\[
W = \frac{1}{1-r} \int_0^1 u_i(a_i, \theta)di
\]

\[
= -\int_0^1 (a_i - \theta)^2 di
\]

They show that \( W \) will decrease as \( \alpha \) increases, if and only if

\[
\frac{\beta}{\alpha} > \frac{1}{(2r-1)(1-r)}.
\]

In this study, I will examine information accuracy

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

which is the expected value of the social welfare \( W \). Moreover, I will also examine information dispersion, which has been absent in Morris and Shin (2002). Define
Dispersion \equiv (E[\int_0^1 (a_i - \bar{a})^2 d_i])^{0.5}

where $\bar{a}$ is the average of $a_i$. Then,

\[
Dispersion \equiv \left( E[\int_0^1 (a_i - \bar{a})^2 d_i] \right)^{0.5}
= \left( E[\int_0^1 (kx_i y - k \bar{x} - (1 - k)y)^2 d_i] \right)^{0.5}
= \left( E[\int_0^1 (kx_i - k \bar{x})^2 d_i] \right)^{0.5}
\]

where $\bar{x} = \int_0^1 x_j dj$. Because $E[\int_0^1 (x_i - \bar{x})^2 d_i]$ is the variance of $x_i$ (i.e., $\frac{1}{\beta}$), equation (4) becomes

\[
Dispersion = \frac{(1 - r)}{\sqrt{\beta(1 - r) + \alpha \beta}}
\]

Therefore, as $\alpha$ increases, dispersion will decrease.

However, Morris and Shin (2002) regard private information precision $\beta$ as exogenous. I will extend their model by endogenizing $\beta$. The extended model can then analyze how the interaction between public and private information affects information dispersion.


Suppose that private information is costly and that the common cost function is given by

\[
C_i = \phi \beta_i
\]

for some $\phi > 0$. Each agent will choose his own optimal level of private information precision. The optimal level of $\beta$ in the symmetric equilibrium can be derived through the following two steps: First, the optimal action $\hat{a}_i$ for agent $i$ is derived, given that his private signal precision is $\beta_i$ and that all other agents have the same private signal precision $\bar{\beta}$. Second, given $\bar{\beta}$, the optimal level of private signal precision ($\hat{\beta}_i$) is
solved for agent $i$. $\hat{\beta}_i$ is then set equal to $\overline{\beta}$ to derive the equilibrium precision ($\hat{\beta}$) of private signal for all agents in the symmetric equilibrium.

Given $\beta_i$ and $\overline{\beta}$, assume the payoff function is the same as in equation (1). Under the assumption that all agents other than agent $i$ have the same level of private signal precision $\overline{\beta}$, the optimal action for agents will still be

$$\hat{a}_j = kx_j + (1-k)y, \text{ for } j \neq i$$

where $k$ is

$$k = \frac{\overline{\beta}(1-r)}{\overline{\beta}(1-r) + \alpha}.$$  

The first order condition for agent $i$ is the same as in equation (2):

$$\hat{\alpha}_i = (1-r)E_i[\theta] + rE_i[\overline{\alpha}]$$

where

$$E_i[\theta] = \frac{\alpha y + \beta_i x_i}{\alpha + \beta_i}$$

and

$$E_i[\overline{\alpha}] = kE_i[\theta] + (1-k)y$$

$$= k \frac{\alpha y + \beta_i x_i}{\alpha + \beta_i} + (1-k)y$$

where $k$ takes the value in equation (6).

When agent $i$ chooses $\hat{a}_i$ as in equation (7), his expected payoff at $\theta$ is

$$E[u_i(\hat{a}_i, \theta)] = E[-(1-r)(\hat{a}_i - \theta)^2 - r\left(\int_0^1 (\hat{a}_j - \hat{a}_i)^2 \, dj - \overline{L}\right)]$$

Because that

$$\hat{a}_j = kx_j + (1-k)y, \text{ for all } j \neq i$$

and that $x_j$ is independent of $x_i$ for $j \neq i$, 

Moreover, because agent $i$ is only one out of the continuum of agents, $\hat{a}_i$ will not affect $E[\bar{L}]$. Therefore equation (8) becomes

$$E[u_i(\hat{a}_i, \theta)] = E[-(\hat{a}_i - \theta)^2] + r \int_0^1 2E[(1-k)(y-\theta)(\hat{a}_i - \theta)] dj - B \quad (9)$$

where $B$ includes terms that do not depend on $\hat{a}_i$:

$$B \equiv r\left(\frac{k^2}{\beta} + \frac{(1-k)^2}{\alpha} - \bar{L}\right).$$

Plug in $\hat{a}_i$ from equation (7), then equation (9) becomes

$$E[u_i(\hat{a}_i, \theta)] = -\frac{(1-r)^2(\bar{B} + \alpha)^2}{(\beta(1-r) + \alpha)^2(\alpha + \beta_i)} - \frac{r^2\alpha}{(\bar{B}(1-r) + \alpha)^2} - B.$$

One can see that as $\beta_i$ goes up, the expected payoff to agent $i$ increases. Therefore, agent $i$ has the incentive to get private signal with higher precision. However, there is the production cost ($C$) of getting private signal. Agent $i$ will then choose $\beta_i$ by maximizing the following payoff that includes both the benefit and the cost of more precise private signal:

$$V(\beta_i) \equiv E[u_i(\hat{a}_i, \theta)] - C$$

$$= -\frac{(1-r)^2(\bar{B} + \alpha)^2}{(\beta(1-r) + \alpha)^2(\alpha + \beta_i)} - \frac{r^2\alpha}{(\bar{B}(1-r) + \alpha)^2} - B - \phi \beta_i.$$

The first order condition for maximizing $V(\beta_i)$ implies that agent $i$ will choose the following optimal level of $\beta_i$:

$$\hat{\beta}_i = \frac{(1-r)(\bar{B} + \alpha)}{\sqrt{\phi}(\bar{B}(1-r) + \alpha)} - \alpha \quad (10)$$

with the constraint that $\hat{\beta}_i \geq 0$. If $\alpha < \frac{1-r}{\sqrt{\phi}}$, then $\hat{\beta}_i \geq 0$. 

50
To derive the private signal precision \( \hat{\beta} \) for all agents in the symmetric equilibrium, \( \hat{\beta}_i \) is set equal to \( \bar{\beta} \) in equation (10). Then

\[
\hat{\beta}_i = \bar{\beta} = \frac{1}{\sqrt{\phi}} - \frac{\alpha}{1-r}.
\]

When \( \alpha < \frac{1-r}{\sqrt{\phi}} \), \( \hat{\beta} \) in the symmetric equilibrium is

\[
\hat{\beta} = \frac{1}{\sqrt{\phi}} - \frac{\alpha}{1-r}.
\]

However, if \( \alpha \geq \frac{1-r}{\sqrt{\phi}} \), then \( \hat{\beta} = 0 \) in the symmetric equilibrium. This study assumes that \( \alpha < \frac{1-r}{\sqrt{\phi}} \). Therefore, equation (11) suggests that higher precision of public signal will crowd out the acquisition of private signal in the equilibrium.

3. Information Accuracy and Dispersion

In the symmetric equilibrium, equation (3) suggests that the action of agent \( i \) is:

\[
\hat{a}_i = k x_i + (1-k)y
\]

where

\[
k = \frac{\hat{\beta}(1-r)}{\hat{\beta}(1-r) + \alpha}.
\]

So information accuracy, \(-E[(\hat{a}_i - \theta)^2]\), in the equilibrium is:

\[
-E[(\hat{a}_i - \theta)^2] = -\frac{\alpha + \hat{\beta}(1-r)^2}{(\alpha + \hat{\beta}(1-r))^2} = -\sqrt{\phi} - \frac{\alpha \phi}{(1-r)^2}.
\]

Then higher precision of public signal will actually decrease information accuracy.

Recall that information dispersion in equation (5) is
\[ Dispersion = \frac{(1-r)}{\sqrt{\beta(1-r) + \frac{\alpha}{\sqrt{\beta}}}}. \]

Replacing \( \beta \) in equation (5) with \( \hat{\beta} \), then information dispersion in the symmetric equilibrium is:

\[ Dispersion = \sqrt{\phi^{0.5} - \frac{\phi\alpha}{1-r}}. \tag{12} \]

which suggests that increased precision of public signal will decrease information dispersion.

How does the crowding out between \( \alpha \) and \( \hat{\beta} \) affect the impact of \( \alpha \) on information dispersion? If there were no crowding out (i.e., \( \hat{\beta} \) did not depend on \( \alpha \)), then equation (5) suggested the net effect of \( \alpha \) on dispersion was:

\[ \frac{\partial Dispersion}{\partial \alpha} = -\frac{\sqrt{\hat{\beta}(1-r)}}{(\hat{\beta}(1-r) + \alpha)^2}. \tag{13} \]

If there is crowding out, then equation (5) suggests the net effect of \( \alpha \) on dispersion is:

\[ \frac{dDispersion}{d\alpha} = -\frac{\sqrt{\hat{\beta}(1-r)}}{(\hat{\beta}(1-r) + \alpha)^2} + \frac{\partial}{\partial \hat{\beta}} \left( \frac{\sqrt{\hat{\beta}(1-r)}}{\hat{\beta}(1-r) + \alpha} \right) \frac{\partial \hat{\beta}}{\partial \alpha}. \tag{14} \]

Equation (14) has an extra term compared with equation (13). Because of the crowding out effect (i.e., \( \frac{\partial \hat{\beta}}{\partial \alpha} < 0 \)), if

\[ \frac{\partial}{\partial \hat{\beta}} \left( \frac{\sqrt{\hat{\beta}(1-r)}}{\hat{\beta}(1-r) + \alpha} \right) < 0 \]

which holds when \( \alpha < \frac{(1-r)}{2\sqrt{\phi}} \), then the crowding out will shrink the marginal impact of \( \alpha \) on information dispersion. However, when \( \alpha > \frac{(1-r)}{2\sqrt{\phi}} \), the crowding out will amplify the marginal impact of \( \alpha \) on information dispersion.
### Appendix II: IAS

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<th>IAS Items</th>
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<td>IAS 1 Presentation of Financial Statements</td>
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<td>IAS 2 Inventories</td>
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<td>IAS 7 Cash Flow Statements</td>
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<tr>
<td>IAS 8 Profit or Loss for the Period, Fundamental Errors and Changes in Accounting Policies</td>
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<td>IAS 10 Events After the Balance Sheet Date</td>
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<td>IAS 11 Construction Contracts</td>
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<td>IAS 12 Income Taxes</td>
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<td>IAS 14 Segment Reporting</td>
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<td>IAS 15 Information Reflecting the Effects of Changing Prices</td>
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<td>IAS 20 Accounting for Government Grants and Disclosure of Government Assistance</td>
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<td>IAS 21 The Effects of Changes in Foreign Exchange Rates</td>
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<td>IAS 22 Business Combinations</td>
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<td>IAS 26 Accounting and Reporting by Retirement Benefit Plans</td>
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<td>IAS 27 Consolidated Financial Statements and Accounting for Investments in Subsidiaries</td>
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<td>IAS 32 Financial Instruments: Disclosures and Presentation</td>
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Note: International Accounting Standards (IAS) were issued by the IASC from 1973 to 2000. The IASB replaced the IASC in 2001. Since then, the IASB has amended some IAS, has proposed to amend other IAS, has proposed to replace some IAS with new International Financial Reporting Standards (IFRS), and has proposed certain new IFRS on topics for which there was no previous IAS. The IAS includes the following: