# How Country-Level Corporate Governance Impacts Information Environment. Using a New Model with More Forecast Properties

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## Abstract

*Financial analyst forecast properties are often used to measure the information environment (IE) within which firms operate. The three most common analyst proxies for IE are analyst following, analyst forecast accuracy, and analyst forecast dispersion. Research using these forecast properties indicates that country-level corporate governance (CCG) positively affects IE. However, consider that analyst properties are determined by both public and private information and that these proxies do not enable determining these two dimensions; even so, they can be interpreted as a rough proxy for IE, in particular because there are models that measure the proportion and precision of private information, the precision of public information and the precision of total information using analyst data. We claim that it is especially important to understand these dimensions and that the relationship between CCG and IE has not been fully investigated. The aim of this paper is therefore to investigate this relationship more thoroughly using a new model as a proxy for firms' IE. We use a worldwide sample, and our results show that higher levels of CCG significantly and positively affect IE. Greater CCG improves the precision of both public and total information. Additionally, our results indicate that precision in private information is unaffected by greater CCG and that analysts use relatively less private information in their forecasts with increased CCG. We can therefore conclude a generally positive relationship between CCG and IE with improved public information.*

**Keywords**: information environment, analyst forecasts, comparative study

## *1. Introduction*

Analyst forecast properties are often used to measure the information environment (IE) within which firms operate. The three most common analyst proxies for IE are analyst following, analyst forecast accuracy, and analyst forecast dispersion. These three measures have been used widely in the literature to examine how different aspects affect the firm´s IE, and they have also been used widely to examine how country-level corporate governance (CCG) affects IE (see, for example, Bhat et al. 2006; Chang et al. 2000; Hope 2003a; Barniv et al. 2005; von Koch et al. 2014a). However, to gain a better understanding of how CCG affects IE, we argue that these three measures are not sufficient. The aim of this paper is therefore to investigate this relationship more thoroughly by using a model that can analyse the proportion of private information and the precision of private, public and total information at the same time. By using the model, we are able to better understand the various implications of different CCG laws on firms´ IE. Earlier studies have found when CCG is strong, accounting information can play a more important role, and analysts rely to a greater extent on public financial accounting information (e.g., Hope et al. 2009). For example, it has been reported that earnings forecasts have greater usefulness in countries that are characterised by strong legal environments, which are considered to support strong corporate governance (Chang et al. 2000; Ashbaugh and Pincus 2001; Hope 2003a; 2003b; Barniv et al. 2005; Barniv and Myring 2006; DeFond et al. 2007). Multiple studies differentiate between common and civil law countries based on the assumption of a correspondence with strong vs. weak corporate governance. Chang et al. (2000) found that analysts' forecasts were more accurate and forecast dispersion was lower in common-law countries. Their argument is that common-law countries generally have more effective CCG mechanisms, including stronger shareholder protection.

Barniv et al. (2005) found that analysts in common-law countries outperform their peers in civil-law countries. They suggest an association between legal and financial reporting environments and analysts´ forecasts. Bhat et al. (2006) also discuss how greater compliance with rules and regulations should reduce analysts' uncertainty about financial reports and, in turn, make the task of forecasting earnings relatively easier. Additionally, von Koch et al. (2014a), who used a longitudinal measure of CCG, found that analysts' performance was better with higher degrees of investor protection. However, it is important to stress that none of these studies, although it is well-known that analysts use both private and public information in their forecasts, take this into account. We therefore have, so far, no knowledge of whether CCG improves the quality of public or private information or both, which this study will contribute to determining. There is also the background that existing theory suggests a relationship between the precision of private and public information but neither theory nor empirical work supports one direction of the association (Botosan et al. 2004). Therefore, the present study also contributes to understanding whether public and private information are complements to or substitutes for each other.

We use a worldwide sample, and our results show a positive and significant relationship between higher levelsof CCG and IE. Greater CCG improves the precision of both public and total information. Additionally, our results indicate that precision in private information is unaffected by greater CCG and that analystsuse relatively less private information in their forecasts with increased CCG. We can therefore conclude a generally positive relationship between CCG and IE with improved public information. The present study thus confirms earlier results that found a positive relationship between CCG and IE (see, for example, Bhat et al. 2006; Chang et al. 2000; Hope 2003a; Barniv et al. 2005),but more importantly, it deepens the understanding of IE by demonstrating that the positive relationships supported only by better precision in public information. Our results indicate that higher levelsof CCG only improve the public information (financial reports, etc.) that analysts can access but not the quality of private information. These results do not support the notion that public and private information are complements. Additionally, our results indicate that the proportion of private information is negatively related to CCG; analysts appear to cease gathering private information with improved public information quality. We proceed as follows. We review the literature in Sect. 2. We discuss our data and methodology in Sect. 3. We provide our main results in Sect. 4 and perform robustness tests in Sect. 5, and we summarise our study and discuss implications in Sect. 6.

## *2. Literature Review*

### 2.1 CCG and Financial Analysts

Within the line of research from country-level perspectives, there has been a stream of comparative governance literature (initiated by the work of La Porta et al. 1998, 1999) focused on how economies, capital markets and firms perform under different legal regimes. One explanation is that CCG influences the role of accounting information in the market. In countries with strong CCG, investors rely more on financial accounting information because it is perceived as more trustworthy (e.g., Hope et al. 2009). This also indicates that earnings forecasts are perceived as more trustworthy and therefore have greater usefulness in these countries (Chang et al. 2000; Ashbaugh and Pincus 2001; Hope 2003a; 2003b; Barniv et al. 2005; Barniv and Myring 2006; DeFond et al. 2007). Another explanation is that strong CCG influences analysts to perform better because there is greater demand for higher-quality earnings reports. Countries with strong CCG are assumed to have highly developed capital markets in which earnings information is considered to be more valuable and relevant than it is in less refined markets (e.g., Barniv et al 2005; DeFond et al. 2007). These explanations are supported by a number of empirical studies that have also found an assumed relationship between CCG and legal origin. Chang et al. (2000), for example, found that analysts' forecasts are more accurate and forecast dispersion is lower in common-law countries. Their explanation is that common-law countries in general can be characterised by more effective corporate governance. Barniv et al. (2005) found that analysts in common-law countries performed better than their peers in civil-law countries, which, according to the authors, is evidence of the existence of an association between legal and financial reporting environments and analysts´ forecast behaviour. This association is also related to the enforcement of and compliance with law and regulations. Prior research has shown that common law countries have stronger enforcement of accounting standards than do civil law countries (Francis et al. 2003; Hope 2003a). Hope (2003a) argues that strong enforcement of accounting standards encourages (or forces) managers to follow the accounting rules that are in place (thereby reducing analysts' "accounting uncertainty"). Bhat et al. (2006) also discuss how greater compliance with rules and regulations should reduce analysts' uncertainty about financial reports and, in turn, somewhat simplify the task of forecasting earnings.

All of the studies cited above support their results by referring to other research that shows reported earnings to be more useful to analysts in stronger rather than weaker CCG countries (e.g., Alford et al 1993; Ali et al. 2003; Ball et al. 2000; Hung 2000; Leuz et al. 2003; Hail and Leuz. 2006). If reported earnings are more useful in strong CCG countries, investors demand earnings-related information, thus giving analysts an incentive to provide superior earnings forecasts. These studies suggest an association between legal and financial reporting environments and analysts' forecasts. The main argument of these studies is that strengthening CCG improves firms' public information, which can lead to a decreased need for analysts to obtain private information. If more information is known by an outsider, an insider has less private information, which affects analysts' gathering of private information. However, these assumptions have not been sufficiently empirically tested.

Another area of research related to the present study is studies that do not examine CCG directly but rather, investigate the disclosure of CCG. Bushman et al. (2004) argue, for example, that corporate transparency varies systematically with a country's legal/judicial environment. According to Bushman and Smith (2001), one reason for this is that the effectiveness of accounting information in limiting expropriation by minority investors is likely to be greater when investors appears to have stronger protection. To the extent that CCG disclosure affects the quality of the accounting reports that analysts use to generate forecasts and that the quality of these reports is linked to the degree to which the reported figures (such as earnings) will persist into the future, analysts will be able to issue more accurate forecasts by learning about a firm's governance through disclosure. For example, analysts who are aware of the effects of weak governance on disclosure might rely less on the reported financial figures of a firm with weak governance and instead use other sources of information (e.g., direct communication with managers, including whisper forecasts) to generate more accurate forecasts. In contrast, they might be more inclined to use the provided accounting information when formulating forecasts for firms that appear to have strong governance mechanisms in place. Thus, we could reasonably expect that analysts in weak legal environments use less accounting information than do those in strong legal environments.

Based on prior research, it appears to be reasonable to assume that analysts 'performance improves with stronger CCG. At the same time, it is also reasonable to assume that there is a substitution effect between CCG and financial analysts' performance. With increased CCG, performance improves, but at the same time, because of the increased quality of information, the demand for financial analysts is reduced. This implies that there is a basis for a more refined analysis of the relationship, particularly because these this results are in line with those of Heflin et al. (2003) and Irani and Karamanou (2003), who argue that if analysts seek to gain an advantage by collecting private information in response to improved public information, this improved public information may improve accuracy while simultaneously increasing dispersion.

### 2.2 IE and Financial Analysts

Financial analysts' properties are widely used to study elements of IE. Revsine et al. (2004) and Schipper (1991) argue that analysts should be seen as among the most significant users of financial statements and among the most important intermediaries between companies and investors. Unlike "regular" investors, analysts have the ability to interpret accounting information in a sophisticated manner (eg, Schipper 1991). Jensen and Meckling (1976) suggest that analysts can serve as effective monitors of manager behaviour through their information-gathering activities and thereby reduce agency costs arising from the separation of ownership and control. Analysts 'earnings forecasts have been used to interpret market expectations of firm performance because investors' expectations are unobservable, and their performance hasbeen a proxy for the efficiency of financial markets. That is, for example, if analysts use financial statements with greater information content and are thereby able to issue better forecasts, it is hence possible to measure IE using those forecasts (Chang et al. 2000; Barniv et al. 2005; Ashbaugh and Pincus 2001; Hope 2003a; 2003b; Barniv and Myring 2006; Defond et al. 2007; Sun 2009; Lang et al. 2004; von Koch et al. 2014a; 2014b). Researchers have also been interested in the split between private and public information in analysts' forecasts. There are two competing arguments about how analysts' private information changes if the public information increases. A field of studies based on Kim and Verrecchia (1991) finds that public information supersedes private information and therefore private information is reduced when more public information reaches the market. Another line of studybased on Kim and Verrecchia (1997) arguesthat better public information can affect analysts' incentives to collect and issue forecasts based on private information. The private information in analysts' forecasts is not entirely a natural result of more public information, but analysts need more time to collect, process, and analyse large amounts of publicly available information and combine this with private information.

If they must spend more time gathering and processing their data, they must necessarily reduce the number of companies they analyse owing to their limited time and resources. Multiple studies also show that this substitution occurs (Knyazeva 2007; Sun 2009; von Koch et al. 2014a; 2014b). Recently, models have been developed to divide analysts' estimates of private and public information (Barron et al. 2002; Sheng and Thevenot 2012), and these models have been used by a number ofresearchers (see, among others, Kim and Shi 2012; Beuselinck et al. 2010; Byard et al. 2011; Yang 2011 and von Koch et al. 2014c) to increase the understanding of IE. The model that first went by the acronym BKLS but has since been modified by Sheng and Thevenot (2012) allows for capturing, among other things, total, public and private information and the proportionsof private information in analysts' forecasts.

## *3. Method*

### 3.1 CCG Index

We use a shareholder protection index (SPI) that measures CCG by the levels of shareholder protection laws and regulations. Compared with earlier, more well-known indexes such as legal enforcement and LLSV, the SPI makes it possible to perform time-series analyses of CCG and thereby study CCG changes more effectively than before. The index, developed by the Corporate Governance Research Programme at the Centre for Business Research, University of Cambridge, UK (see Armour et al. 2009, Lele and Siems 2007), measures the strength of legal shareholder protection in a given country for each year, thereby allowing researchers to investigate changes over time in a single country. In addition to making time-series analysis possible, the SPI is also more refined than, for example, the well-known LLSV index in regard to the number of variables that can be accommodated, and it addresses a number of problems for which the LLSV has been criticised (Armour et al. 2009).

### 3.2 Measuring Analyst Forecast Properties

Analyst forecast properties are often used to measure the IEs within which firms operate (see a similar discussion in von Koch et al. 2014c). The three most common analyst proxies for IE are analyst following, analyst forecast accuracy, and analyst forecast dispersion. These three measures have been used widely in the literature to examine how different aspects affect firms’ IEs, and these analyst forecast properties have also been used widely to examine how (CCG) affects IE (see for example Bhat et al. 2006; Chang et al. 2000; Hope 2003a; Barniv et al. 2005). Researchers are especially interested in estimating forecast accuracy and uncertainty about future earnings. Measuring uncertainty is challenging because it is unobservable. Therefore, researchers have attempted to use alternative proxies for earnings forecast uncertainty. Forecast dispersion (measured as the standard deviation in analysts’ forecasts), which can be used to indicate the extent of analysts’ disagreement regarding a firm’s upcoming earnings, can be used as a proxy for investor uncertainty prior to the release of key information (Ramnath et al. 2008).

As seen above, forecast dispersion among analysts is one of the most commonly used measures of earnings forecast uncertainty (see for example, Clement et al. 2003; Yeung 2009). Forecast dispersion is simpleto calculate, and it also uses a measure of the uncertainty when the forecast is made as a proxy for uncertainty and therefore has a number of advantages. However, some researchers (see, for example, Abarbanell et al. 1995; Johnson 2004) note that this measure does not capture uncertainty to a full extent. Indeed, dispersion represents only one part of forecast uncertainty, namely, that arising from analysts’ private information and the diversity of forecasting models. Therefore, dispersion is an unreliable and noisy proxy for earnings forecast uncertainty when analysts’ collective uncertainty becomes dominant or when the change in uncertainty is the most important measure. Resolving this deficiency could be said to be the basis for the development of the BKLS model proposed by Barron, Kim, Lim and Stevens (1998). According to this model, uncertainty can be estimated as the sum of dispersion and the squared error in the mean forecast. The model recognises that uncertainty is composed of two elements, public and private information, and that the quality of these components can be measured. The logic behind the BKLS model’s method of measuring quality is that forecast dispersion and the error in the mean forecast are functions of the quality of public information, the quality of private information, and the number of analysts following a company. By reversing these functions, it is possible to infer public and private information quality dispersion, error in the mean forecast, and the number of forecasts, and this will make it possible to assess the quality of public and private information using the following equations:

$$h = \frac{\mathrm{SE} - \frac{\mathrm{D}}{\mathrm{N}}}{\left[\left(1 - \frac{1}{\mathrm{N}}\right)\mathrm{D} + \mathrm{SE}\right]^2}, \qquad s = \frac{\mathrm{D}}{\left[\left(1 - \frac{1}{\mathrm{N}}\right)\mathrm{D} + \mathrm{SE}\right]^2},$$

$h$ = the quality (precision) of public information
$s$ = the quality (precision) of private information
*SE* = the expected squared error in the mean forecast
*D* = the expected sample variance (or dispersion) in forecasts
*N* = the number of forecasts

In the equations, the quality of common information is denoted by $h$ and the quality of the private information is denoted by $s$. There is also an opportunity to measure the quality of total information, $k$, using these two equations; measuring information quality is performed by summing$h$ and $s$. Additionally, it is possible to measure the relative use of private information $p$ by dividing $h$ by $h + s$. BKLS suggests that one can use observed dispersion and mean squared error as proxies for D and SE to empirically estimate the constructs in equations. Because it is based on information available to analysts at the time the forecasts are made, observed forecast dispersion appears to be an effective proxy for its expected counterpart, D. However, using actual earnings to estimate SE may pose a serious problem because forecast errors are known to analysts only after the announcement of actual earnings.

However, there have been recent claims that using the BKLS measure as a proxy for *ex ante* uncertainty is problematic. According to Sheng and Thevenot (2012), BKLS only provides an estimate of *ex post* uncertainty because forecast errors are known to respondents only after actual earnings are announced, and thus the measure itself is highly uncertain. Sheng and Thevenot (2012) also criticise the BKLS model for being extremely affected by significant unanticipated events following forecasts and because it relies on the assumption that actual earnings are exogenous, which is unlikely to hold in practice; there is an extensive stream of research showing that managers manipulate earnings to meet or exceed analysts' forecasts. Sheng and Thevenot(2012) therefore suggest a revised model. Specifically, to alleviate the issues associated with using an *ex post* estimate of SE, the authors suggest using a GARCH model to estimate the squared error of the mean forecast using historical data only. In particular, this method uses the time series of errors in the mean forecast to estimate their conditional variance. After estimating using the GARCH model, one can obtain the conditional variance, which is then used as an estimate in the expressions above. Henceforth, we refer to this model as the ST model.

Although on the surface, the new model appears to make only small changes, it is suggested to have multiple benefits compared with the older version. For example, the new measure of uncertainty, compared with other existing measures in the literature that have been used to evaluate changing CCG, better captures both components of the theoretical construct, and it is more stable and reliable in a variety of settings. It also has the advantage that it is based on information known to analysts at the time they make forecasts rather than estimates. To fulfil our aim, we therefore use this model that was designed to measure the proportion of private information and the precision of private, public information and total information at the same time. We thereby expand analyst properties with more sophistical proxies for a firm´s IE. The earlier version of the model (BKLS) has been used in many prior studies that analysed analysts (see, among others, Kim and Shi 2012; Beuselinck et al. 2010; Byard et al. 2011; Yang 2011 and von Koch et al. 2014c) but not for analysing CCG's effect on analyst properties. The later version (ST) has not been widely used as yet, and it has of course not been used to analyse CCG' simpact on analyst properties. Both of these models are, however, based on financial analysts' data and are aimed at measuring firms' IEs. The only study that has used the new model (Barron et al. 2012) concludes that it is superior to BKLS. For example, the study finds that information asymmetry and average information precision are more important factors than equity beta and firm size in determining firms' capital costs. The seemingly great importance of these variables is not apparent when using the BKLS measure in the same way as it is when using the ST model.

### 3.3 Variables and Research Design

Analysts typically forecast the earnings per share (EPS) of a particular fiscal year multiple times before releasing their actual figures, and the frequency of forecasts differs by analyst. The Institutional Brokers' Estimate System (IBES) collects forecast data from individual analysts around the world once a month and uses those data to calculate statistics such as means, medians, and standard deviations. Only the analysts' final estimates are included in the monthly calculations.

Thus, the IBES database provides calculated statistics of analysts' EPS forecasts once a month. In this study, we utilise the general methodology for collecting forecast data (see, for example, Lang and Lundholm 1996) using the final calculated means of an analyst's EPS forecasts before the first quarterly EPS report is released. For example, for a firm with a fiscal year end of December 31, 2013, we use the mean forecast calculated in March 2013 as the forecast data for the actual EPS on December 31, 2013. We use these basic data to calculate SE, the conditional variance, the expected sample variance and the number of forecasts in the ST model. The six control variables (see Table 3), which were selected based on prior research on factors that normally affect analysts' performance (Lang and Lundholm 1996, von Koch et al. 2014a), are as follows: number of analysts, market value, trading volume, earnings surprise, profit/loss, and the standard deviation of return on equity (std ROE).

**Table 1: Independent Variables**

| Variable | Explanation | Predicted sign of the dependent variables |
|---|---|---|
| Number of analysts | The number of analysts following a company. | + |
| Market value | The company's market value at the beginning of the fiscal year. | + |
| Trading volume | The company's absolute daily trading volume during the first month of the fiscal year. | + |
| Profit/Loss | A dummy variable that takes the value of 1 if the company reported a loss and 0 otherwise. | - |
| Earnings surprise | The absolute value of the year's earnings per share**,** minus the previous year's earnings per share, scaled by the share price at the beginning of the fiscal year**.** $EPS_t$ is the earnings per share during period t (of a given year), and $EPS_{t-1}$ is the earnings per share in period t-1 (the previous year). | - |
| Std ROE | The company's standard deviation return on equity over the previous three years. | - |
| CCG | Our variable of main interest (shareholder protection variable SPI). | + |

Note: This table explains the independent variables and their predicted signs.

The number of analysts is determined by counting the analysts who follow a company and providing earnings forecasts in the month for which we are collecting data, again in line with Lang and Lundholm (1996). We control for firm size using market value and trading volume. There are a number of motives in the literature behind controlling for firm size. Size should reflect information availability and therefore be positively related to forecast accuracy. Brennan and Hughes (1991) also found empirical evidence of a relationship between firm size and number of analysts following a firm, and Lang and Lundholm (1993) found that firm size and performance variability likely correlate with disclosure policy. Market value is measured as the company's market value at the beginning of the fiscal year and is commonly used to control for size. However, we also utilise trading volume as a control for size because it may be more indicative of the number of analysts following a firm because analysts are often paid indirectly through trading activity. Trading volume refers to the company's absolute daily trading volume during the first month of the fiscal year. Earnings surprise, which is the variation in a firm's results from one year to another, is calculated as the absolute value of the year's earnings per share minus the previous year's earnings per share, scaled by the share price at the beginning of the fiscal year**.** $EPS_t$ is the earnings per share during period t (of a given year), and $EPS_{t-1}$ is the earnings per share during period t-1 (the previous year).

$$\text{EarningsSurprise} = \frac{\left|EPS_t - EPS_{t-1}\right|}{\text{Stock price at the beginning of the fiscal year}}$$

According to Lang and Lundholm (1996), earnings surprise controls for the likely effects of major events, such as a firm's introduction of a new product, on forecasts. In these circumstances, realised earnings are most likely to deviate from expected earnings, and it is likely that analysts will not be able to make accurate forecasts.

Hope (2003a) suggests that it is much more difficult to predict future earnings for firms with negative earnings. We therefore use a control variable, loss, as a dummy variable that has a value of 1 if the company reported a loss and 0 otherwise. King et al. (1990) found that the number of analysts following a firm is likely to be related to variations in returns. Fewer analysts follow firms that experience significant fluctuations in profitability. In other words, a negative relationship exists between the number of analysts and variations in profitability. Thus, the standard deviation of return on equity is the final control variable in our regressions, and it is measured as the company's return on equity over the previous three years.

### 3.4 Sample and Descriptive Statistics

Using the ST model, we need to use a GARCH model to estimate the conditional variance. We thus require a long time series and therefore only select firms with a consecutive 15 years or more of analyst forecasts. Our final sample consists of 16,156 observations, as seen in the last column in Table 2, from publicly traded companies in 21 countries.

**Table 2: Descriptive Statistics**

| | N | h | s | k | p | SPI | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | N (SPI) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Argentina | 9 | 0.15 | 0.01 | 0.17 | 0.88 | 3.80 | 3 | 3 | 3.75 | 3.75 | 3.75 | 3.75 | 4 | 4.6 | 4.6 | | | 9 |
| Brazil | 299 | 1.04 | 3.58 | 4.53 | 0.57 | 4.95 | 4.75 | 4.75 | 3.75 | 3.75 | 4.75 | 4.75 | 5.25 | 5.5 | 5.5 | 5.5 | 5.5 | 250 |
| Canada | 869 | 3.01 | 7.70 | 11.02 | 0.62 | 6.75 | 6.75 | 6.75 | 6.75 | 6.75 | 6.75 | 6.75 | 6.75 | 6.75 | 6.75 | 6.75 | 6.75 | 745 |
| Chile | 177 | 1.15 | 3.12 | 4.44 | 0.67 | 3.24 | 2.25 | 2.25 | 2.25 | 2.25 | 2.25 | 2.25 | 4.25 | 4.25 | 4.25 | 4.25 | 4.25 | 158 |
| China | 137 | 1.84 | 0.89 | 3.29 | 0.77 | 6.09 | 5 | 5 | 5.75 | 5.75 | 5.75 | 5.75 | 6 | 6.4 | 6.6 | 6.6 | 6.6 | 109 |
| Czech Republic | 32 | 1.55 | 3.98 | 5.52 | 0.53 | 3.85 | | | | 3 | 3 | 3 | 4.25 | 4.25 | 4.25 | 4.25 | 4.25 | 25 |
| France | 1,223 | 1.98 | 5.07 | 7.11 | 0.56 | 7.07 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7.25 | 7.25 | 7.25 | 1,036 |
| Germany | 394 | 1.95 | 3.38 | 5.33 | 0.63 | 5.37 | 3.583 | 3.583 | 3.583 | 4.167 | 4.167 | 4.167 | 5.167 | 5.667 | 5.667 | 6 | 6.25 | 295 |
| India | 29 | 1.93 | 6.40 | 8.33 | 0.30 | 5.70 | | 5 | 5 | 5.25 | 5.25 | 5.5 | 6.125 | 6.125 | 6.125 | 6.125 | 6.125 | 25 |
| Italy | 581 | 1.69 | 2.19 | 4.37 | 0.69 | 4.48 | 3.25 | 3.25 | 3.25 | 4.75 | 4.85 | 4.85 | 4.85 | 5 | 5 | 5.15 | 5.15 | 498 |
| Japan | 280 | 1.08 | 0.66 | 1.74 | 0.87 | 7.16 | 7.25 | 7.25 | 7.25 | 7.25 | 7.25 | 7.25 | 7.25 | 7 | 7 | 7 | 7 | 242 |
| Malaysia | 285 | 1.69 | 3.80 | 5.56 | 0.51 | 2.69 | 5.75 | 5.75 | 5.75 | 5.75 | 6 | 6 | 6.25 | 6.25 | 6.25 | 6.25 | 6.25 | 267 |
| Mexico | 301 | 1.58 | 2.66 | 4.23 | 0.66 | 6.01 | 2 | 2 | 2 | 2 | 2.25 | 2.25 | 3.375 | 3.375 | 3.375 | 3.375 | 3.375 | 245 |
| Netherlands | 847 | 2.79 | 4.56 | 7.39 | 0.68 | 2.12 | 1.75 | 1.75 | 1.75 | 1.75 | 1.75 | 1.75 | 1.75 | 1.75 | 1.75 | 2.75 | 5 | 725 |
| South Africa | 68 | 4.42 | 8.67 | 13.13 | 0.64 | 5.47 | 5.417 | 5.417 | 5.417 | 5.417 | 5.417 | 5.417 | 5.417 | 5.417 | 5.667 | 5.667 | 5.667 | 58 |
| Spain | 576 | 2.76 | 5.61 | 9.20 | 0.54 | 5.06 | 4.75 | 4.75 | 4.75 | 5 | 5 | 5 | 5 | 5 | 5.5 | 5.5 | 5.5 | 488 |
| Sweden | 494 | 1.86 | 2.11 | 4.03 | 0.70 | 3.95 | 3 | 3.5 | 3.75 | 3.75 | 3.75 | 3.75 | 4.25 | 4.25 | 4.25 | 4.25 | 4.75 | 420 |
| Switzerland | 778 | 2.00 | 3.20 | 5.22 | 0.73 | 4.78 | 4.25 | 4.25 | 4.25 | 4.75 | 4.75 | 4.75 | 4.75 | 5.25 | 5.25 | 5.25 | 5.25 | 660 |
| Turkey | 265 | 0.71 | 0.61 | 1.20 | 0.89 | 5.24 | 4.5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5.7 | 5.7 | 5.7 | 208 |
| UK | 1,440 | 4.55 | 8.79 | 13.61 | 0.53 | 6.76 | 6.5 | 6.625 | 6.625 | 6.625 | 6.625 | 6.625 | 6.625 | 6.625 | 6.625 | 7.375 | 7.375 | 1,215 |
| US | 10,006 | 4.55 | 9.07 | 14.38 | 0.69 | 6.60 | 6.25 | 6.25 | 6.25 | 6.25 | 6.25 | 6.25 | 6.25 | 7 | 7.25 | 7.25 | 7.25 | 8,478 |
| Total | 19,090 | 3.56 | 7.04 | 11.09 | 0.66 | 6.02 | 5.67 | 5.66 | 5.66 | 5.75 | 5.78 | 5.73 | 5.84 | 6.26 | 6.44 | 6.58 | 6.71 | 16,156 |

Table 2 shows the means for our main variables. The average precision for common information for the total sample is 3.56, whereas average precision is 7.04 for private information. The total sample also shows that the relative use of private information is 0.66. Table 3 shows great variation between countries for these main variables. For example, the UK and the US have the highest precision of common information (4.55), whereas Argentina has the lowest (0.15), which is also true for the precision of private information (UK 8.79, US 9.07 and Argentina 0.01). The relative use of private information varies from 0.30 in India to 0.89 in Turkey. Table 2 also shows the development of our CCG variable (SPI) over the time period 1995 to 2005 in our 21 countries. The average CCG for the total sample strengthened from 5.67 in 1995 to 6.71 in 2005. However, the development of CCG during this time period differed for individual countries, as seen in Table 2.

### 3.5 Models and Estimation Techniques

We estimate the following equation:

$$Q_{\theta}(\text{h, s, k, p}_{it}) = \alpha + \beta_1 \text{Number of analysts}_{it} + \beta_2 \text{Market value}_{it} + \beta_3 \text{Trading volume}_{it}$$
$$+ \beta_4 \text{Profit/Loss}_{it} + \beta_5 \text{Earnings surprise}_{it} + \beta_6 \text{Std dev ROE}_{it} + \beta_7 \text{(SPI) CCG}_{it}$$
$$+ \beta + \varepsilon_{it}$$

Where Number of analysts is the number of analysts who make forcasts of a company. Market value is measured as the company's market value at the beginning of the fiscal year. Trading volume refers to the company's absolute daily trading volume during the first month of the fiscal year. Profit/Lossis a dummy variable that takes the value of 1 if the company reported a loss and 0 otherwise. Earnings surprise is the absolute value of the year's earnings per share minus the previous year's earnings per share, scaled by the share price at the beginning of the fiscal year. Std ROE is the company's standard deviation return on equity over the previous three years.

All continuous variables are winsorised at the 1st and 99th percentiles, and we use logarithm transformation for our analysis. All of these variables are regressed respectively with the independent variables h (COMMON information), s (PRIVATE information) and k (TOTAL information), estimated using the ST model.

## *4 Results*

Table 3 provides the correlations for all of the variables. All four of our dependent variables are significantly correlated with each other. The values for the precision of common (h), private (s) and total information (k) are positively correlated, indicating a relationship in which an increase in one correlates with an increase in another. One interpretation is thus that increased public information leads to increased private information using the ST model. The two types of information thereby complement each other. Additionally, both private and common information correlate positively, as was expected with total information. In contrast, the relative use of private information (p) correlates significantly negatively with the other three variables, h, s and k, indicating that with the increased precision of common and private information, analysts use relatively less private information. When examining our variable of interest, SPI (CCG), we find a significant positive correlation between SPI and the precision of common (h), private (s) and total information (k) and a significant negative correlation with relative use of private information (p). This is an indication that CCG matters for information environments using the ST model. The table also shows the six control variables. An unexpected finding is that Market value did not strongly correlate with the four dependent variables, and Trading volume appears to mainly correlate negatively with the dependent variables. Loss, Earnings surprise and Std ROE correlate significantly negatively with the precision of common (h), private (s) and total information (k). These latter correlations all occur in the expected direction, as observed earlier in Table 1. Loss-making and volatility in profitability worsen the information environment, causing analysts to begin using relatively more private information (there was a significant positive correlation with p). The signs also indicate some interesting aspects stemming from the number of analysts who follow a company. Increased numbers of analysts following a company does not impact the precision of public information, although it improves the precision of private and also total information. More analysts following a company also leads analysts to use relatively less private information. There are no problems with multicollinearity because the highest correlation among the independent variables is 0.33 (for trading volume and number of analysts).

**Table 3: Correlations Matrix**

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Common - h | 1.00 | | | | | | | | | | |
| 2. Private - s | 0.34*** | 1.00 | | | | | | | | | |
| 3. Private proportion - p | -0.12*** | -0.63*** | 1.00 | | | | | | | | |
| 4. Total - k | 0.67*** | 0.89*** | -0.51*** | 1.00 | | | | | | | |
| 5. SPI | 0.11*** | 0.12*** | -0.02** | 0.13*** | 1.00 | | | | | | |
| 6. Market value | -0.01 | 0.02* | -0.01 | 0.01 | -0.08*** | 1.00 | | | | | |
| 7. Trading volume | -0.04*** | -0.00 | -0.05*** | -0.02* | -0.06*** | 0.22*** | 1.00 | | | | |
| 8. Loss | -0.13*** | -0.12*** | 0.13*** | -0.14*** | -0.01 | -0.02*** | -0.01 | 1.00 | | | |
| 9. Earnings surprise | -0.08*** | -0.11*** | 0.10*** | -0.11*** | -0.15*** | -0.07*** | 0.19*** | 0.15*** | 1.00 | | |
| 10. Std ROE | -0.10*** | -0.09*** | 0.07*** | -0.11*** | 0.03*** | -0.06*** | 0.04*** | 0.21*** | 0.07*** | 1.00 | |
| 11. Following | -0.01 | 0.06*** | -0.12*** | 0.03*** | -0.15*** | 0.13* | 0.33*** | -0.09*** | -0.07*** | -0.06*** | 1.00 |

$^{***}p < 0.001.$ $^{**}p < 0.01.$ $^{*}p < 0.05.$

Notes: This table shows the correlations between all of the dependent and independent variables.

Table 4 shows our four regressions. Column 1 shows the regressions with COMMON information; column 2 shows PRIVATE information; and column 3 shows TOTAL information. Column 4 shows regressions with the relative use of private information. The CCG variable SPI is highly significant ($p<0.001$) in three models, showing that stronger CCG improves the precision of public and total information; the last column, however, shows that CCG negatively affects the relative use of private information. However, as the second column shows, we find no significant relationship between CCG and the precision of private information. The control variables are also good predictors of information environments. Market value is highly significant in all four regression, showing that analysts increase the precision of public, private and total information when they forecast larger firms at the same time that they use relatively less private information. Trading volume shows a similar pattern to that of market value, and the control variables Loss, Earnings surprise and Std ROE show expected results.

In general, the precision of analysts' public, private and total information worsens for loss-making firms and firms with variation in earning and profitability.

At the same time, analysts use relatively more private information for these firms. Finally, the control variable Following shows that an increase in the number of analysts generally improves the precision of public, private and total information and at the same time, analysts use relatively less private information when more analysts are following a company. Therefore, we also run a separate regression (not shown in the table) with Following as a dependent variable and found a substitution effect; that is, greater CCG decreases the number of analysts. In sum, our independent variable and control variables in general show the results that were expected from Table 1.

**Table 4: OLS Regressions**

| Variable | COMMON - h | Private - s | Total – k | Proportion - p |
|---|---|---|---|---|
| CCG | 0.086*** | 0.061 | 0.129*** | -0.023*** |
| | (5.70) | (1.91) | (7.40) | (-3.39) |
| Market value | 0.034** | 0.128*** | 0.103*** | -0.036** |
| | (2.50) | (4.33) | (6.45) | (-5.70) |
| Trading volume | 0.051*** | 0.062** | 0.016 | -0.016** |
| | (4.29) | (2.43) | (1.14) | (-2.91) |
| Loss | -1.520*** | -2.415*** | -1.784*** | 0.327*** |
| | (-19.90) | (-14.67) | (-20.09) | (9.33) |
| Earnings surprise | -0.023 | -0.124*** | -0.095*** | 0.030*** |
| | (-1.58) | (-3.97) | (-5.71) | (4.62) |
| Std ROE | -0.309*** | -0.508*** | -0.383*** | 0.066*** |
| | (-19.55) | (-14.78) | (-20.76) | (9.03) |
| Following | 0.011** | 0.044*** | 0.019*** | -0.006*** |
| | (3.78) | (6.78) | (5.42) | (-4.12) |
| Constant | -1.286*** | -4.114*** | -1.249*** | -0.055 |
| | (-9.42) | (-13.88) | (-7.84) | (-0.87) |
| N | 15.799 | 15.629 | 16.156 | 15.905 |
| R-squared | 0.08 | 0.06 | 0.09 | 0.04 |
| F-statistics | 76.96*** | 57.57*** | 98.28*** | 38.35*** |
| Fixed effects (Year) | Yes | Yes | Yes | Yes |

$^{***}p < 0.001.^{**}p < 0.01.^{*}p < 0.05.$

Note: This table shows the results from our four regressions. Column 1 shows the regressions with COMMON information; column 2 shows PRIVATE information; and column 3 shows TOTAL information. Column 4 shows the relative use of private information.

## *5. Robustness Analysis*

As an alternative procedure, we also estimated our equations using median regressions. Because OLS is sensitive to skewness and outliers in the sample, all of the continuous variables were winsorised at the 1st and 99th percentiles and we took logarithm transformation for our analysis. When running median regressions as a robustness analysis, we do not winsorise or take logarithm transformations of the variables. The results from the median regressions are shown in Table 5. The median regression results confirm our main earlier results regarding our independent variable SPI (CCG), which is still highly significant (p<0.001) for the precision of public and total information. However, we now find no significance for the relative use of private information, and the precision of private information becomes significant (p-value 0.05) in the median regressions. Additionally, the median regressions show differences concerning our control variables. Our size variables (Market value and Trading volume) now become generally insignificant. However, Loss and Following show the same results as in the OLS.

Overall, the median confirms our results for our main variable of interest that greater CCG improves the precision of public and total information while casting doubt on the effect on the precision and relative use of private information. Note, however, that the coefficient for the latter variable is still negative in the median regression.

**Table 5: Median Regressions**

| Variable | COMMON - h | Private - s | Total – k | Proportion - p |
|---|---|---|---|---|
| CCG | 0.109*** | 0.063* | 0.386*** | -0.001 |
| | (5.24) | (2.11) | (5.75) | (-0.11) |
| Market value | 0.000 | -0.000 | -0.000 | 0.000 |
| | (-0.76) | (-0.70) | (-1.66) | (1.77) |
| Trading volume | -0.000 | -0.000 | -0.000 | -0.000 |
| | (-1.24) | (-0.04) | (-0.09) | (-1.59) |
| Loss | -0.910*** | -0.588*** | -2.527*** | 0.111*** |
| | (-8.60) | (-3.65) | (-7.41) | (5.87) |
| Earnings surprise | -0.468 | -0.348* | -1.298*** | 0.094*** |
| | (-4.35) | (-2.24) | (-3.74) | (4.89) |
| Std ROE | -0.013*** | -0.007* | -0.039*** | 0.001** |
| | (-5.45) | (-2.15) | (-5.18) | (3.01) |
| Following | 0.027*** | 0.043*** | 0.088*** | -0.008*** |
| | (7.30) | (8.30) | (7.56) | (-12.46) |
| Constant | 0.607*** | -0.133 | 0.474 | 0.875 |
| | (3.61) | (-0.55) | (0.87) | (29.16) |
| N | 16.156 | 16.156 | 16.156 | 16.156 |
| Pseudo R-squared | 0.02 | 0.01 | 0.02 | 0.04 |
| Fixed effects (Year) | Yes | Yes | Yes | Yes |

$^{**}p < 0.001$. $^{**}p < 0.01$. $^{*}p < 0.05$.

Note: This table shows the results from our four median regressions. Column 1 shows the regressions with COMMON information; column 2 shows PRIVATE information; and column 3 shows TOTAL information. Column 4 shows the relative use of private information.

## *6. Conclusions and Discussion*

We find that higher levels of CCG are significantly positive for two dimensions of IE: Greater CCG improves the precision of public and total information. We also find evidence that the proportion of private information is related to CCG; analysts appear to use relatively less private information when CCG is stronger. Overall, the present study thus confirms earlier results showing a positive relationship between CCG and IE (see, for example, Bhat et al. 2006; Chang et al. 2000; Hope 2003a; Barniv et al. 2005). More importantly, the study deepens the understanding of IE by proving that the positive relationship is supported by greater precision in both public and private information. Our results therefore indicate not only that higher levels of CCG improve public information (financial reports, etc.) but also that also analysts, owing to the improved public information, use less private information in their forecasts. These results support the notion that public and private information can substitute for each other (Kim and Verrecchia 1991). Additionally, our results indicate that the proportion of private information is negatively related to CCG. Therefore, analysts appear to cease gathering private information when the quality of public information is improved. Using more sophisticated proxies for IEin the present study than those from earlier studies leads us to strongly question some of the earlier proxies for IE, such as analyst following, analyst forecast error, and forecast dispersion. For example, the number of analysts following a company is a common proxy for IE (see for example Maffett 2012; Upadhyay and Zeng 2014; Haß et al. 2014; Cang et al. 2014; Johnson and Marietta-Westberg 2009).

However, our results indicate the opposite and arein line withearlier research that found a substitution effect, i.e., that analysts' role is magnified where CCG is weak (see, for example, Knyazeva 2007; von Koch et al. 2014a; Sun 2009) because it appears that analysts are in greater demand when IE is poor; thus, using the number of analysts who follow a company as a proxy for IE could be misleading.

Furthermore, one of our results is the highly negative relationship between the relative use of private information and the number of analysts following a company. One could expect that analysts would attempt to obtain more private information when the competition among them is high, i.e., when more analysts are present in the market. However, these results indicate that greater CCG leads to fewer analysts and that fewer analysts leads to the use of relatively more private information, with better-quality private, and public, information. Analyst forecast error has been used in a number of studies to proxy for IE (see, for example. Giraldo 2011; Haß et al. 2014;Brown and Fernando 2011;Upadhyay and Zeng 2014). We do not criticise this proxy directly, but by showing that analysts 'forecasts contain both private and public information, our study offers a deeper understanding of how CCG affects IE. Another common proxy used to measure IE is forecast dispersion (see for example Maffett 2012; Haß et al. 2014; Francis et al. 2006). This proxy is also questionable becauseit could be related to the relative use of private information. Forecast dispersion could be used to indicate how analysts are using private information (Heflin et al 2003; Irani and Karamanou 2003). If public information is the primary source, there should be less dispersion because of the better quality of such information, which is available to all analysts. However, if analysts seek to gain advantage by gathering private information in response to better-quality public information, the effect would then be increased dispersion. In other words, improved IE can lead to both decreased and increased forecast dispersion. Therefore, because the studies that use forecast dispersion as a proxy for IE do not take into the account the relative use of private information, as we do, forecast dispersion is an unsuitable proxy for IE. IE is important because it is highly related to asymmetric information and the quality of information, both of which are the basis of a market economy. Therefore, the relationship between CCG and IE is also important for policy makers as well as researchers to understand; it is important for both to understand how changes in shareholder protection could influence IE. We argue that we contribute to this knowledge by using better proxies for IE than earlier studies used. Our limitations stem from these proxies because they are merely proxies and thereby can be criticised regarding correctly measuring IE. Future research can develop even better proxies for IE.

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