

# 資訊透明度與分析師預測準確性 --產業層面觀點

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## 摘要

本研究由產業層面探討資訊透明度與分析師預測準確性之關連性，以美國上市公司為研究對象，樣本資料取自 1991-2008 Compustat 及 I/B/E/S 的年度財務報表資訊。實證結果發現產業相關的資訊，確實會影響分析師的預測準確性，包括產業集中度越高時，分析師的盈餘預測準確性越低，而政府有提供經濟誘因的產業，則分析師盈餘預測準確性越高。最後，當產業內其他成員已提供的資訊，越會同步影響其他未提供資訊成員時，意謂著產業內資訊移轉效果較高，此時分析師盈餘預測準確性也會越高，且當產業中充滿越多新資訊時，分析師基於維持良好聲譽或成為意見領袖考量，會更積極透過私有管道以取得獨特資訊，因此有助於提高盈餘預測準確性。

**關鍵詞:** 產業層面觀點、分析師盈餘預測、盈餘預測準確性

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# Information Transparency and Analysts' Forecasts Accuracy - An Industry Perspective

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## Abstract

This paper examines the relationship between information transparency and analysts' forecast accuracy on the basis of industry. Using data from Compustat and I/B/E/S, we provide evidence indicating that the accuracy of analysts' earnings forecasts is lower for firms in more concentrated industries. We further discover that firms belonging to industries with government economic incentives are associated with higher forecast accuracy. With industry-level information transfer effect variable, the more information that is common to all industry members, the higher the analysts' forecast accuracy. Additionally, more industry-level news also enables analysts to conduct more efficient evaluations of a firm's future prospects. Overall, the results indicate that higher transparency within the industry will allow analysts to forecast with higher accuracy, which will then increase market demand for analysts' reports. Thus, in the governance process of raising information transparency, competent authorities should also consider options for fostering transparency at the industrial level.

**Keywords:** *Industry-Level Perspective; Analysts' Earnings Forecasts; Earnings Forecast Accuracy*

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## 1. INTRODUCTION

Security analysts play an important role in financial markets by collecting, analyzing, and disseminating information (Moyer, Chatfield, and Sisneros, 1989; Howe, Unlu, and Yan, 2009). Moyer et al. (1989) and Womack (1996) showed that analysts' recommendations on information content and their earnings forecasts serve as an important reference for investment decisions. Analysts, therefore, not only play the role of information intermediary but also serve as an external mechanism of corporate governance.

Previous literature tends to focus on personal reputation and the conflict of interests for underwriter analysts to explore the forecasting behavior of analysts (e.g., Stickel, 1992; Michaely and Womack, 1999; Beckers, Steliaros, and Thomson, 2004). However, Keane and Runkle (1998) report that in a given specific time, the earnings forecast errors among firms are actually related in the same industry. Furthermore, there are significant differences in analysts' forecasting accuracy across industries. In other words, industry-level characteristics should be the determining factors of analysts' earnings forecasts.

Lang and Lundholm (1996) examine the relationship between the discretionary disclosures of firms and the properties of analysts' earnings forecasts. The results show that firms with more informative disclosure policies have more accurate analyst earnings forecasts. This is identical to most of the studies which discuss information transparency's influence on analysts' reports from the standpoint of the company level (e.g., Yu, 2010 ). This study differs from those studies by employing an industry perspective to explore the effect of information transparency on analysts' forecast accuracy. Additionally, based on studies of the information transfer effect, Cairney and Pantzalis (2002) examine industry-level information transfer effect on managements' earnings forecasts; nevertheless, the relation between industry-level information transfer effect and analysts' earnings forecasts has not been discussed. This study, based on the industrial competitive structure, discusses the information transparency observable within a free-competition market and a government-regulated market. After which, the paper then investigates information transparency under the existing effect of industry information transfers. Hence, three hypotheses are developed to examine, respectively, the effects of industry concentration, the effects of an industry receiving or not receiving

government economic incentives, and the effects of industry-level information transfer (including common information, industry-level news, firm-specific information, and industry homogeneity) on the accuracy of analysts' earnings forecasts. Our study not only encompasses a more complete view of industry-level characteristics, but also helps us to understand the influence of industry-level information transparency on analysts' earnings forecasts.

Our empirical evidence yields several findings. First, the accuracy of analysts' earnings forecasts is lower for firms in more concentrated industries. We further find that firms belonging to industries with government economic incentives are associated with higher forecast accuracy. With regards to the industry-level information transfer effect variable, we find the more information that is common to all industry members, the higher the analysts' forecast accuracy. In addition, more industry-level news also leads to a more efficient evaluation of a firm's future prospects of the analysts. Overall, our results suggest that from an industry-level perspective, information transparency is associated with analysts' forecast accuracy.

The contributions of this study to the development of theory are as follows: 1) The information transparency of individual companies and the industrial level are both significant factors determining earnings forecasts, and these two factors are still under close and continual attention from researchers such as Bonsall, Bozanic, and Fischer (2013); Cready and Gurun (2010); and Shivakumar (2010). However, the studies on the industrial perspective are still insufficient by comparison. Thus, this research aims to enhance the study of information transparency's influence on earnings forecasts from an industrial perspective. 2) Building on the reason mentioned in statement 1, and due to the supplementary and competitive relations between the management's and analysts' earnings forecasts in the capital market, this paper can complete Cairney and Pantzalis' study (2002) by discussing the impact of the industry information environment on analysts' earnings forecasts, an impact which has not yet been thoroughly analyzed. 3) Compared with Cairney and Pantzalis' study (2002) which only explores industry-level information transfer effect, this paper investigates the aspects of industry concentration, the presence or absence of government economic incentives, and industry-level information transfer effect. Such an approach allows the paper to more precisely interpret the influence of information transparency by targeting analysts' earnings forecasts from the industry-level perspective.

In the next section of this paper, we present empirically testable hypotheses. In Section III, we explain the research design and the variable measurement. In Section IV, we describe the sample and discuss the results. We then provide concluding comments in Section V.

## **2. RELATED STUDIES AND HYPOTHESES DEVELOPMENT**

Security analysts can be perceived as the gatekeepers of capital markets because they gather and analyze information from various sources and then relay recommendations to other stock market participants (Aerts, Cormier, and Magnan, 2008). Howe et al. (2009) showed that analysts often use both market- and industry-level information sets to make their recommendations.

Simon and Shallone (2013) indicated that, in most cases, the development and changes of industries are determined by constantly innovative techniques and knowledge, and the market competition structure can account for the reason why enterprises invest in the advancement of innovation and technique. Since this study addresses an industry-level perspective, it will be based on the starting point of the industry competition structure to examine industry information transparency's influence on the accuracy of analysts' earnings forecasts within the context of both a free-competition market and a government-regulated market. The study will then go further and explore industry-level information transfer effect on the accuracy of analysts' earnings forecasts. As a result, the industrial characteristics under study include industry concentration, industry with or without government economic incentives, and whole industry-level information transfer effect (which is sub-divided into the following four measurement variables: common information, industry-level news, firm-specific information, and industry homogeneity).

An industry can be regarded as concentrated when most of the sales produced in that industry are generated by a small number of companies. The lower the industry concentration, the higher its competitiveness will be (Gallego-Álvarez, García-Sánchez, and Rodríguez-Domínguez, 2008). In a free competition market, the urge to stand out in the industry and create competitive advantages will promote the innovation of products and services; therefore, the innovation speed will be fast (Geroski, 1990). Companies actively signal proprietary messages to differentiate themselves from their rivals which will further promote the level of information transparency in an industry.

In sum, we predict that industry concentration is an important factor in the information environment associated with analysts' forecast accuracy. Since lower industry concentration results in higher competitiveness among companies and greater information transparency in an industry, the accuracy of analysts' earnings forecasts will be higher. Thus, we propose the following hypothesis H1 (stated in alternate form).

**H1:** Industry concentration is negatively associated with the accuracy of analysts' earnings forecasts.

Government policy, regulation, and enforcement are major forces in the external business environment (Mahon and Murray, 1981; Marsh, 1998; Shaffer, 1995). For social welfare and economic development purposes, governments usually impose more regulations on specific industries (Greer, 1987; Breyer, 1990). Baron (2000) depicted one end of the government regulation continuum as industries where the government exercises considerable control over opportunities such as telecommunications and biotechnology. At the other end of the spectrum of government regulation are industries where opportunities are more often controlled by markets, and where the government exercises relatively little control over firms and their activities, such as consumer electronics and retail establishments.

Generally speaking, the enterprise that monopolizes the market will have higher capabilities to innovate because of its accumulated experiences and more profound knowledge of the industry; it is therefore entitled to the benefits of enjoying a larger economic scale and can also enjoy most of the innovative profit. Even if the monopolizing enterprise does not continue to innovate, it can still enjoy a large market share; nevertheless, Schumpeter (1976) pointed out that in a monopolized market, the monopolizing enterprise is induced to invest more innovative activities since it can generate a large sum of profit through innovation. On the other hand, constant innovation can also raise the entry barriers for other competitors. This study argues that for industries with government economic incentives, the profits earned are stable; furthermore, such industries can enjoy most of their earnings through innovative profit within a lower competitive industry environment due to higher entry barriers and protective policies. Nevertheless, if the monopolizing enterprises are unwilling to voluntarily publicly disclose their earnings forecasts, financial analysts are still able to obtain various forms of industrial development information from the economic incentive policies provided

by the government. These transparent government policy will also greatly improve the accuracy in speculating earnings forecasts for monopolizing enterprises. In other words, a relatively lower uncertain industrial information environment and a higher level of transparent government policy will boost the accuracy of earnings forecasts.

In sum, the lower the entry barriers are, the higher the market competition and the lower the margin of profit will be. Alternatively, industries with high technology barriers and greater capital needs are regulated by the government. In this case, incentive regulation mechanisms would provide more powerful incentives for regulated firms to reduce costs, improve service quality in a cost effective way, stimulate (or at least not impede) the introduction of new products and services, and encourage efficient investment in and pricing of access to regulated network infrastructure services. In other words, productivity, infrastructure investment, profit levels, and new service offerings have increased under incentive regulation (Kridel, Sappington, and Weisman, 1996). Thus, we predict that industries with government economic incentives enjoy well-regulated protection and a more stable operating environment. Therefore, tracking regulatory developments and policy notices can improve analysts' forecast accuracy. With this in mind, we propose hypothesis H2 as follows (stated in alternate form):

**H2:** The accuracy of analysts' earnings forecasts in industries with government economic incentives is higher than that of analysts' earnings forecasts in industries without government economic incentives.

There is a growing body of evidence to test whether earnings announcements impact the stock prices of reporting firms' non-announcing industry peers (e.g., Firth, 1976; Foster, 1981; Clinch and Sinclair, 1987; Han and Wild, 1990, and Freeman and Tse, 1992). The conclusion of all of these previous studies showed that earnings-related news events are associated with statistically significant transfers of information from announcing to non-announcing firms.

Schipper (1990) also indicated that information transfers occur when an announcement made by one firm contemporaneously provides information about the performance and value of one or more non-announcing firms. That is to say, if the information is common to all industry members, then the performance of the member firms will be affected in a similar way. Stakeholders can extrapolate the information from the disclosing firm to other industry members (King, Pownall, and

Waymire, 1990).

All in all, the information transfer studies mentioned above report that the stock prices of non-disclosing industry members are affected by the release of an earnings forecast by other member-firms, which implies that an industry-level information transfer effect is likely to exist. We infer that if the within-industry “information transfers” exist, then security analysts become more informed about non-disclosing firms’ expectations as a result of the disclosures from other industry members. In the event of common information, analysts learn that new information would have a common impact on the performance of an industry member. We propose hypothesis H3a as follows (stated in alternate form):

**H3a:** The common information in industries is positively associated with the accuracy of analysts’ earnings forecasts.

New information obtained by industry members is disclosed to outsiders in order to update their beliefs about earnings expectations (King et al., 1990). Once released, the information is available to everyone at low or no cost and may affect the behavior of stakeholders, thus leading them to modify their information needs or to reassess their economic interests.

Even though the influence on the company's cash flow will not last too long, the more news within an industry, the more uncertain it is. Under this circumstance, individual companies will be unlikely to publicly issue the relevant operation opportunities and risks (Miller 2002); therefore, we can infer that when the transparency of industrial information is low, analysts will have less information available to search via public channels. Furthermore, the analysts will be unable to forecast the news according to the historical data or trends. All these factors push analysts to actively search information through private channels which would increase the accuracy of earnings forecasts in order to maintain the analyst's reputation and role as a leading analyst. We propose hypothesis H3b as follows (stated in alternate form):

**H3b:** Industry-level news is positively associated with the accuracy of analysts’ earnings forecasts.

Following this line of information transfers, if news only influence a particular company, it is firm-specific information. If companies wish to stand out from their competitors, voluntary disclosure is one possible way to achieve this distinction.



Thus, companies with good performance are willing to disclose private information in order to separate themselves from other companies; that is, decreasing the information asymmetry could adjust the incorrect expectations or beliefs of the investors. Analysts can then acquire the information easier and combine such information with other public information in order to re-estimate a company's performance and ranking within the industry. Thus, more firm-specific information could also lead to a more efficient evaluation of a firm's future prospects by the analysts. We propose hypothesis H3c as follows (stated in alternate form):

**H3c:** Firm-specific information in industries is positively associated with the accuracy of analysts' earnings forecasts.

The more consistent the influence on the specific information within an industry, the lower the cost for the management to disclose the information; even if inaccurate information is issued, it will be considered as a common good or bad news within the industry by the capital market participants, and the belief will be projected to the company's value whether disclosed or not. This will abate the fluctuations of the entire industry market reaction, and the analysts' earnings forecasts will be more accurate. Thus, we propose hypothesis H3d as follows (stated in alternate form):

**H3d:** The level of industry homogeneity is positively associated with the accuracy of analysts' earnings forecasts.

### **3. EMPIRICAL DESIGN AND VARIABLE MEASUREMENT**

#### **3.1 Data and Sample Description**

Our sample data include all U.S. publicly traded companies. The data of industry characteristics, financial statement variables, and earnings forecasts are from the Compustat and I/B/E/S during the period from 1991 to 2008. We restrict our sample to all non-financial firms with available data in each four-digit SIC group per year because banking and financial institutions (four-digit SIC codes 6000 and 6500) have different financial reporting regulations. Furthermore, we delete the observations for which financial data and earnings forecasts are unavailable in the Compustat and I/B/E/S, and earnings per share winsorized at 5 (-5). After those sample selection procedures, it yields a final sample of 5,030 firm-year observations. Table 1 describes the sample selection procedure.

**Table 1 Sample Selection Procedure**

Step	N
Data of all listed companies in IBES or Compustat from 1991 to 2008	141,538
Goals:	
1. Merging data of IBES and Compustat by Ticker	135,492
2. Restricting Sample	312
3. Deleting missing data	704
Final entire sample	5,030

Note: N represents the firm-year level observations.

### 3.2. Variables Measurement

#### 3.2.1 Measuring Proxy of Analysts' Earnings Forecast Accuracy

In order to explore the relationships between industry-level characteristics and the accuracy of analysts' earnings forecasts, our measure for the forecast accuracy ( $ACCY_t$ ) is calculated as the negative of the absolute value of forecast error scaled by stock price in period  $t-1$ . Following Lang and Lundholm (1996), we define forecast accuracy as the negative of the absolute forecast error so that more accurate forecasts are represented by higher values. In Equation (1), we denote  $FORECAST_t^{t-1}$  as the mean I/B/E/S consensus forecast earnings per share in period  $t$  during the period starting two months before the corresponding actual earnings per share announcement and ending three days before the announcement. According to the regulations of IFRS, we define  $EPS_t$  as actual earnings per share after extraordinary items in period  $t$ , taken from Compustat, and  $PRICE_{t-1}$  is the stock price in period  $t-1$ . The forecast accuracy is expressed in the following equation:

$$ACCY_t = (-1) \left| \frac{FORECAST_t^{t-1} - EPS_t}{PRICE_{t-1}} \right| \quad (1)$$

#### 3.2.2 Measuring Proxies of Industry-Level Information Transfer Effect

We use the four proxies of industry-level information transfer effect ( $ILE$ ) developed by Cairney and Pantzalis (2002), the degree of industry concentration ( $HI$ ), and the industry with economic incentives ( $IEI$ ) to examine how different industry-level characteristics influence the accuracy of analysts' earnings forecasts. As shown in the study of Cariney and Pantzalis (2002), the proxies of  $ILE$  include industry-level news ( $ILN$ ), industry homogeneity ( $IH$ ), common information ( $CI$ ) and firm-specific information ( $FSI$ ). Following this line approach, we define the

industry-level earnings surprise as the *ILN* for measuring the impact of industry-level news on firm performance. First, we calculate the firm-level earnings surprise (*LN*) by the following equation:

$$LN_{i,t} = |AE_{i,t} - AE_{i,t-1}| \quad (2)$$

where  $LN_{i,t}$  represents the firm-level earnings surprise;  $AE_{i,t}$  represents the actual earnings of firm  $i$  in period  $t$ ;  $AE_{i,t-1}$  represents the actual earnings of firm  $i$  in period  $t-1$ . Then, we measure the industry-level news (*ILN*) by summing all firms' earnings surprise in the same industry.

$$ILN_t = \sum_{i=1}^n LN_{i,t} \quad (3)$$

Furthermore, as suggested by Cairney and Pantzalis (2002), we could not distinguish the differences in performance of members in an industry by using the new information while the reported earnings of all industry members are similarly affected by the same information. Thus, we use the industry homogeneity (*IH*) to measure whether new information has a similar effect on the earnings of all members in an industry. The definition of *IH* is the mean of the 4-digit SIC industry member correlations of annual changes in earnings over the period 1991 to 2008. We expect that the higher value of *IH* represents that the new information has a more consistent impact on all members in an industry, which implies that the firms in the industry have higher homogeneity. Furthermore, we calculate common information (*CI*) as the industry homogeneity multiplied by numbers of industry members, and defined as news released by one industry member that can be similarly applied to other industry members. Although the meaning of *CI* and *IH* seems identical, we consider that *CI* and *IH* are used to measure the breadth and average effects of common information on the analysts' forecast accuracy, respectively. Therefore, we suppose that these two variables are different and thus we should consider both variables in an empirical model in order to examine different hypotheses.

Intangible assets would increase the information complexity (Gu & Wang, 2005). A firm with proprietary knowledge-based intangible assets, such as technology development, will reveal rich firm-specific information through the value of these intangible assets. Furthermore, analysts can predict earnings forecasts for firms by placing greater relative emphasis on their own private (or idiosyncratic) information (Barron, Byard, Kile, & Riedl, 2002). In order to examine the relation

between firm-specific information and analysts' forecast accuracy, we defined the proxy of firm-specific information as the percentage of industry members in a year with R&D expenses. Therefore, higher *FSI* represents those industries with more firms reporting R&D expenses, which should result in more new and private information. We expect that analysts cannot accurately forecast the earnings level of firms with greater *FSI*.

With respect to the industry concentration, we employ the following equation to calculate the Herfindahl Index (*HI*).

$$HI_{j,t} = \sum_{i=1}^J S_{i,j,t}^2 \quad (4)$$

where  $S_{i,j,t}$  represents the market share of firm  $i$  in industry  $j$  in period  $t$ . The higher value of *HI* represents that a market is being a monopolized and the lower value of *HI* represents that a market is enjoying perfect competition. In theory, the government will provide specific industries with economic incentives to increase the economic development and competitive power of a country. The information environment and the competition between members in the industry with economic incentive that differs from those in other industries will result in the analysts having different earnings forecasts for that industry. In order to examine whether government-provided economic incentives influence the accuracy of analysts' earnings forecasts, we use the *IEI*, a binary variable, to separate the industry with economic incentives from whole samples. According to the classification of SIC codes, when a firm belongs to the communications industry (SIC codes 4812-4899) or the biotechnology industry (SIC codes 2833-2836), the *IEI* is equal to 1; otherwise, it is equal to 0. It is important to note that the classification method of Foster (1981) using the four-digit SIC codes for classifying each firm is used and followed for the appropriate industry in this study<sup>1</sup>.

### 3.3. Empirical Design

To examine whether industry-level characteristics influence the forecast

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<sup>1</sup> In essence, the *FSI* and *IEI* have different economic meanings in terms of the analysts' forecast accuracy. For example, the meaning of *FSI* for the analysts' forecast accuracy is to measure the degree to which members protected their competitive advantage, while the meaning of *IEI* is to measure the degree to which the government protected an industry's competitive advantage. Even though the percentage of industry members in a year with R&D expenses in communications and biotechnology industries with economic incentives maybe higher than the other industries, we include *FSI* and *IEI* in Equation (5) in order to capture the different effects on the analysts' forecast accuracy.

accuracy, we use the Equation (5) to test our hypotheses H1, H2 and H3:

$$\begin{aligned} ACCY_t = & \alpha_0 + \alpha_1 CI + \alpha_2 ILN + \alpha_3 FSI + \alpha_4 IH + \alpha_5 HI + \alpha_6 IEI + \alpha_7 SIZE \\ & + \alpha_8 Z + \alpha_9 STDROE + \alpha_{10} NUMEST + \alpha_{11} SURPRISE + \alpha_{12} LOSS \\ & + \alpha_{13} EPS + \varepsilon \end{aligned} \quad (5)$$

where *SIZE* represents the logarithm of total assets; *Z* represents the financial distress score developed by Altman's (1968); *STDROE* represents the standard deviation of earnings over the previous two years; *NUMEST* represents the number of analysts following; *SURPRISE* represents the absolute value of the earnings surprise; *LOSS* represents the dummy variable that takes the value of 1 (0) if firm-year observations have positive (negative) earnings; *EPS* represents the earnings per share excluding extraordinary items. The arguments of H3a, H3b, H3c, H3d, and H2 hold while the coefficients of *CI*, *ILN*, *FSI*, *IH*, and *IEI* are significantly positive; furthermore, the coefficient of *HI* is significantly negative which implies that the first hypothesis holds.

In Equation (5), firm size (*SIZE*) is included based on Lang and Lundholm (1996), who document a positive association between firm size and forecast accuracy. Considering that a firm with higher probability of bankruptcy in the future will provide manipulated financial reports or information to deceive investors, we also add the financial distress score (*Z*) developed by Altman (1968) into Equation (4). According to the definition of Altman, the higher (lower) value of *Z* represents that a firm has lower (higher) probability of bankruptcy. Therefore, we expect that the relationship between forecast accuracy and *Z* to be positive. Earnings volatility (*STDROE*) is included based on Kross et al. (1990), who have shown that analysts' earnings forecasts are less accurate for firms with higher long-term earnings volatility. The number of analysts following (*NUMEST*) is included based on Hong and Kubik (2003), who find that financial analysts have great incentives to be the lead analyst and consequently set their forecasts to minimize their average absolute forecast error. As the finding of Lang and Lundholm suggested (1996), we also include the absolute value of the earnings surprise (*SURPRISE*) and expect that larger changes in earnings are associated with less accurate forecasts. The loss indicator variable (*LOSS*) is included based on Hwang, Jan, and Basu (1996), who find that analysts' forecasts for loss-reporting firms are, on average, less accurate than forecasts for profit-reporting firms. Considering that earnings level is related to forecast accuracy (Eames and Glover, 2003), we include the earnings per share (*EPS*)

which excluded extraordinary items based on the regulation of IFRS. To control the presence of heteroscedasticity, we apply White's (1980) heteroscedasticity consistent standard errors for all regression analyses performed in this study.

## 4. EMPIRICAL RESULTS

### 4.1 Sample Characteristics

Descriptive statistics of the regression variables are provided in Table 2. The mean (median) forecast accuracy (*ACCY*) is -0.057 (-0.025) in the sample, suggesting that the mean (median) difference between analysts' forecasts and corresponding actual earnings is about 5.7% (0.25) of the lagged stock price. The average effect of industry-level news on firm performance (*ILN*) is 6.017. The average *FSI* is 0.487, which shows that most of the industries have fewer firms reporting R&D expenses. *IH* shows a mean value of 0.909, suggesting that the average industry homogeneity percentage is about 90.9%. The average degree of industry concentration (*HI*) is 0.359, and *IEI* has the mean value of 0.036, indicating that 3.6% of the sample firm-year observations have received economic incentives from the government. Firm size (*SIZE*), which is the logarithm of the total assets, is 6.567. The mean *Z* is 6.733, implying that our firm-year observations, on average, have lower probability of bankruptcy during the next year. The average earnings surprise (*SURPRISE*) is 1.982 and about 9.2% of the sample observations report loss (*LOSS*) for the year. The mean number of analysts following (*NUMEST*) is 8.646, implying that an average of nine analysts' forecasts covering a firm were included in our sample. The average earnings per share, excluding extraordinary items (*EPS*), is 75 cents.

In Table 3, we report a correlation matrix, which contains Pearson product moment correlation between the regression variables. We find that there are significant positive relationships between *ACCY* and *CI*, and between *ACCY* and *IH*, which implies that to some extent, the accuracy of analysts' earnings forecasts is higher for industries with more common information and higher industry homogeneity. Furthermore, there are negative relationships between *CI* and *HI*, *ILN* and *HI*, *FSI* and *HI*, *IH* and *HI*, as well as *IEI* and *HI*, implying that to some extent, the proxy of industry concentration and the proxies of industry-level information transfer effect are substitute. The evidence in Table 3 reveals that most of the control variables are significantly correlated with the analysts' forecast accuracy

(*ACCY*), and this indicates that firms with larger size, lower volatility of ROE, more analyst followings, higher earnings surprise, positive earnings, and higher EPS have higher accuracy for analysts' earnings forecasts than do other firms.

**Table 2 Descriptive Statistics**

<b>Variable</b>	<b>Mean</b>	<b>Median</b>	<b>Standard Deviation</b>	<b>1st Percentile</b>	<b>99th Percentile</b>
<i>ACCY</i>	-0.057	-0.025	0.101	-0.547	-0.001
<i>CI</i>	44.416	17.342	67.890	-2.000	299.989
<i>ILN</i>	6.017	5.980	1.856	1.702	10.347
<i>FSI</i>	0.487	0.500	0.283	0.000	1.000
<i>IH</i>	0.909	0.987	0.234	-0.189	1.000
<i>HI</i>	0.359	0.315	0.222	0.065	1.000
<i>IEI</i>	0.036	0.000	0.186	0.000	1.000
<i>SIZE</i>	6.567	6.512	1.575	3.111	10.432
<i>Z</i>	6.733	4.670	9.335	0.455	39.113
<i>STDROE</i>	38.997	9.865	116.091	0.150	478.703
<i>NUMEST</i>	8.646	6.000	7.054	1.000	32.000
<i>SURPRISE</i>	1.982	0.546	10.525	-17.155	40.433
<i>LOSS</i>	0.092	0.000	0.289	0.000	1.000
<i>EPS</i>	0.754	0.729	1.228	-3.56	4.22

Variable Definitions:

- ACCY* = accuracy in analysts' earnings forecasts, defined as the negative of the absolute difference between the forecast and actual earnings, scaled by price.
- CI* = common information; defined as news released by one industry member that can be similarly applied to other industry members.
- ILN* = industry-level news; defined as the industry-level earnings surprise.
- FSI* = firm-specific information; measured by the percentage of industry members in a year with R&D expenses.
- IH* = industry homogeneity; defined as the industry associated primarily with common information.
- HI* = industry concentration.
- IEI* = dummy variable that takes the value of 1 (0) if the firm is affiliated with economic incentives (non- economic incentives) industry.
- SIZE* = the logarithm of total assets.
- Z* = financial distress score.
- STDROE* = standard deviation of earnings over the previous two years.
- NUMEST* = the number of analysts following.
- SURPRISE* = absolute value of the earnings surprise.
- LOSS* = dummy variable that takes the value of 1 (0) if firm-year observations have positive (negative) earnings.
- EPS* = the earnings per share excluding extraordinary items.

Table 3 Pearson Correlation Among the Industry-Level Characteristics, Analysts' Earnings Forecast Accuracy, and Control Variables

	<i>ACCY</i>	<i>CI</i>	<i>ILN</i>	<i>FSI</i>	<i>IH</i>	<i>HI</i>	<i>IEI</i>	<i>SIZE</i>	<i>Z</i>	<i>STDROE</i>	<i>NUMEST</i>	<i>SURPRISE</i>	<i>LOSS</i>
<i>CI</i>	0.024*												
<i>ILN</i>	0.004	0.421***											
<i>FSI</i>	-0.022	0.144***	0.201***										
<i>IH</i>	0.044***	0.161***	-0.093***	0.037***									
<i>HI</i>	-0.016	-0.458***	-0.265***	-0.162***	-0.163***								
<i>IEI</i>	0.014	0.295***	0.109***	-0.013	0.026*	-0.071***							
<i>SIZE</i>	0.111***	-0.099***	0.014	0.048***	0.088***	0.093***	-0.088***						
<i>Z</i>	0.046***	0.238***	0.110***	0.118***	0.038***	-0.101***	0.252***	-0.136***					
<i>STDROE</i>	-0.032**	0.038***	0.069***	0.094***	0.013	0.026*	0.003	0.445***	-0.001				
<i>NUMEST</i>	0.069***	0.055***	0.033**	0.075***	0.109***	-0.009	-0.014	0.551***	0.010	0.329***			
<i>SURPRISE</i>	0.039***	0.067***	-0.002	0.001	0.032**	0.001	-0.006	0.198***	0.062***	0.235***	0.215***		
<i>LOSS</i>	-0.150***	0.173***	0.178***	0.136***	-0.110***	-0.061***	0.120***	-0.241***	0.046***	-0.013	-0.101***	-0.100***	
<i>EPS</i>	0.361***	-0.147***	-0.097***	-0.067***	0.053***	0.050***	-0.085***	0.354***	-0.041***	0.107***	0.095***	0.069***	-0.344***

Notes: *ACCY* represents the accuracy in analysts' earnings forecasts and is defined as the negative of the absolute difference between the forecast and actual earnings, scaled by price; *CI* is the proxy of the common information and defined as news released by one industry member that can be similarly applied to other industry members; *ILN* is the proxy of the industry-level news and defined as the industry-level earnings surprise; *FSI* is the proxy of the firm-specific information and measured by the percentage of industry members in a year with R&D expenses; *IH* is the proxy of the industry homogeneity and defined as the industry associated primarily with common information; *HI* represents the degree of the industry concentration; *IEI* is the dummy variable that takes the value of 1 (0) if the firm is affiliated with economic incentives (non-economic incentives) industry; *SIZE* is defined as the logarithm of total assets of firm; *Z* represents the financial distress score; *STDROE* represents the standard deviation of earnings over the previous two years; *NUMEST* is the proxy of the number of analysts following; *SURPRISE* represents the absolute value of the earnings surprise; *LOSS* is the dummy variable that takes the value of 1 (0) if firm-year observations have positive (negative) earnings; *EPS* represents the earnings per share excluding extraordinary items. \*\*\*, \*\*, \* indicate significance at 1%, 5%, and 10% percent levels in a two-tailed test, respectively.



## 4.2 Multivariate Analysis

In column (1) of Table 4, the coefficient on  $HI$  ( $\alpha_5$ ) is negative, while on  $IEI$  ( $\alpha_6$ ) it is positive, which has a significance indicated at  $p < 0.05$  and  $p < 0.01$  separately. This further indicates that an industry with economic incentives and lower degree of industry concentration has a higher level of analysts' forecast accuracy. This evidence implies that H1 and H2 are supported. We infer that these findings may mean that firms belonging to less concentrated industries provide more information, because companies actively signal the differentiating messages so as to separate themselves from their rivals, enabling this different and private information to interflow in the market rapidly and thus raising the industry's information transparency. Information collected by analysts with higher quality and quantity would therefore result in higher accuracy in their earnings forecasts. Meanwhile, there were significant differences in analysts' forecast precision between industries with or without government economic incentives. The main reason for these differences may be attributed to regulation protection resulting in less competition and a more stable operating environment.

The coefficients on our alternative proxies for industry-level information transfer effect,  $CI$  and  $ILN$ , are positively significant at  $p < 0.01$  in columns (2) and (3), but the coefficients of the other proxies of industry-level information transfer effect,  $FSI$  and  $IH$ , are insignificant in columns (4) and (5). This evidence demonstrates that the more information that is common to all industry members and the greater the impact of industry-level news on firm performance, the higher the analysts' forecast accuracy will be. On the contrary, firm-specific information and industry homogeneity have no significant effect on the analysts' forecast accuracy. This evidence implies that H3a and H3b are supported, but H3c and H3d are not supported. In columns (2) and (3), we further find that the effect of  $HI$  disappears when we include industry-level information transfer effects in the regression. However, the degree of industry concentration still results in a negative impact on the analysts' forecast accuracy even when we include  $FSI$  and  $IH$  in the empirical model. This evidence indicates that to some extent, the effect of  $HI$  on the analysts' forecast accuracy is mitigated by the industry-level information transfer effect,  $CI$

and *ILN*. When we include the industry concentration, industries with or without government economic incentives, and industry-level information transfer effect in equation (4), we find that the higher *CI*, *ILN*, and *IEI*, the higher analysts' forecast accuracy. As reported at the end of the table 4, the explanatory power of the models ranges from 13.71 to 14.01%.

The control variables are significant in most cases in columns (1) to (6). Consistent with Lang and Lundholm (1996), the coefficients on *SIZE* are positively significant, which implies that analysts can more accurately forecast larger firms' earnings than smaller firms. We infer that larger firms will disclose more information because investors pay more attention to such firms, and as a result, the analysts can more accurately forecast these firms' earnings. The coefficients on *SURPRISE* and *STDROE* are insignificant throughout different specifications. As in Hwang et al. (1996), the coefficient on *LOSS* is negative in all columns. The coefficients on *Z*, *NUMEST*, and *EPS* are always positively significant. This evidence implies that analysts can more accurately forecast the earnings levels of firms with lower probability of bankruptcy in the next year, more numbers analysts following and higher EPS.

**Table 4 Multivariate Tests on the Association between Industry-level Characteristics and Forecast Accuracy**

$$ACCY_t = \alpha_0 + \alpha_1 CI + \alpha_2 ILN + \alpha_3 FSI + \alpha_4 IH + \alpha_5 HI + \alpha_6 IEI + \alpha_7 SIZE + \alpha_8 Z + \alpha_9 STDROE + \alpha_{10} NUMEST + \alpha_{11} SURPRISE + \alpha_{12} LOSS + \alpha_{13} EPS + \varepsilon$$

	Expected Sign	(1)	(2)	(3)	(4)	(5)	(6)
Intercept		-0.0668 (-7.756)***	-0.0753 (-8.653)***	-0.0677 (-7.908)***	-0.0663 (-7.482)***	-0.0718 (-6.500)***	-0.0775 (-7.002)***
<i>CI</i>	+		0.0001 (4.849)***				0.0001 (4.175)***
<i>ILN</i>	+			0.00001 (3.038)***			0.00001 (1.809)*
<i>FSI</i>	+				-0.0012 (0.265)		-0.0031 (-0.653)
<i>IH</i>	+					0.0056 (0.780)	0.0044 (0.601)
<i>HI</i>	—	-0.0115 (-2.120)**	0.0010 (0.166)	-0.0077 (-1.377)	-0.0118 (-2.124)**	-0.0105 (-1.879)*	0.0019 (0.314)
<i>IEI</i>	+	0.0182 (3.312)***	0.0105 (1.785)*	0.0171 (3.116)***	0.0180 (3.259)***	0.0180 (3.269)***	0.0104 (1.747)*
<i>SIZE</i>	+	0.0028 (1.932)*	0.0026 (1.817)*	0.0030 (2.067)**	0.0028 (1.916)**	0.0029 (1.965)**	0.0028 (1.896)*
<i>Z</i>	+	0.0005 (2.687)***	0.0004 (2.264)**	0.0005 (2.563)**	0.0005 (2.686)***	0.0005 (2.670)***	0.0004 (2.272)**
<i>STDROE</i>	—	-0.00001 (-0.600)	-0.00001 (-0.864)	-0.00001 (-0.740)	-0.00001 (-0.573)	-0.00001 (-0.557)	-0.00001 (-0.817)
<i>NUMEST</i>	+	0.0008 (3.504)***	0.0007 (3.240)***	0.0008 (3.538)***	0.0008 (3.512)***	0.0008 (3.422)***	0.0007 (3.242)***
<i>SURPRISE</i>	—	0.0001 (0.674)	0.00002 (0.220)	0.0001 (0.732)	0.0001 (0.660)	0.0001 (0.672)	0.00002 (0.280)
<i>LOSS</i>	—	-0.0128 (-1.878)*	-0.0150 (-2.202)**	-0.0146 (-2.118)**	-0.0126 (-1.864)*	-0.0123 (-1.779)*	-0.0150 (-2.162)**
<i>EPS</i>	—	0.0301 (13.514)***	0.0304 (13.583)***	0.0302 (13.545)***	0.0300 (13.492)***	0.0300 (13.514)***	0.0304 (13.574)***
Adj. $R^2$		13.73%	14.01%	13.81%	13.71%	13.73%	13.99%
<i>F-test</i>		89.931	82.898	81.599	80.929	81.027	63.933

Notes: *ACCY* represents the accuracy in analysts' earnings forecasts and is defined as the negative of the absolute difference between the forecast and actual earnings, scaled by price; *CI* is the proxy of the common information and defined as news released by one industry member that can be similarly applied to other industry members; *ILN* is the proxy of the industry-level news and defined as the industry-level earnings surprise; *FSI* is the proxy of the firm-specific information and measured by the percentage of industry members in a year with R&D expenses; *IH* is the proxy of the industry homogeneity and defined as the industry associated primarily with common information; *HI* represents the degree of the industry concentration; *IEI* is the dummy variable that takes the value of 1 (0) if the firm is affiliated with economic incentives (non-economic incentives) industry; *SIZE* is defined as the logarithm of total assets of firm; *Z* represents the financial distress score; *STDROE* represents the standard deviation of earnings over the previous two years; *NUMEST* is the proxy of the number of analysts following; *SURPRISE* represents the absolute value of the earnings surprise; *LOSS* is the dummy variable that takes the value of 1 (0) if firm-year observations have positive (negative) earnings; *EPS* represents the earnings per share excluding extraordinary items. \*\*\*, \*\*, \* indicate significance at 1%, 5%, and 10% percent levels in a two-tailed test, respectively. All the t-statistics are based on White's (1980) heteroscedasticity-corrected standard errors by each firm. t-statistic are noted in parentheses below each coefficient estimate.

### 4.3 Sensitivity Analysis

In order to examine the interrelationships among the six proxies of industry-level characteristics and then attempt to explain them in terms of their common underlying dimensions, this research conducted factor analysis to identify a smaller set of prominent factors to take the place of the original set of indicators of industry-level characteristics. We put into action the principal component factor method with a VARIMAX rotation to facilitate interpretations. Table 5 displays factor analysis results with VARIMAX rotation of the six proxies of industry-level characteristics. In this table, we can find that the Kaiser-Meyer-Olkin overall measure of sampling adequacy (MSA) is 0.667 and the overall significance of the correlation matrix is 0.000, with a Bartlett test of sphericity value of 5098.508. This means that the data matrix had sufficient correlation to the factor analysis. These measures indicated that the variables had good predictive power for the dimensions. Therefore, we label *factor 1* as “industry information value” which is comprised by the *ILN*, *CI*, *HI*, *FSI*; we label *factor 2* as “industry government economic incentives” which is comprised by the *IEI*; and we label *factor 3* as “industry industry homogeneity” which is comprised by the *IH* based on the results of factor analysis. We conjecture that the three factors have positive effects on the analysts’ forecast accuracy. As shown in Table 5, these factors have an eigenvalue of at least 1.044, and the cumulative proportion that the three factors contribute to the total variation amounts to 71.855.

Furthermore, we use three factors, “industry information value,” “industry government economic incentives,” and “industry information homogeneity” to take the place of the original set of indicators of industry-level characteristics in Equation (5). In Table 6, we can find that the coefficients on *factor 1* and *factor 2* are positively significant at  $p < 0.01$  in columns (1) and (2), but the coefficient of *factor 3* is insignificant in columns (3). This evidence shows that the more industry information value and government economic incentives, the higher the analysts’ forecast accuracy will be. On the contrary, industry information homogeneity has no significant effect on the analysts’ forecast accuracy. Reported at the end of the table, the explanatory power of the models ranges from 13.62 to 13.87%. The control variables are significant in most cases in columns (1) to (4), which implies that analysts can more accurately forecast the earnings levels of firms with larger size, less earnings surprise, positive earnings, lower probability of bankruptcy in the next year, more numbers of analysts following, and higher EPS. Finally, the results of factor analysis show that the results of multivariate analysis are still robust.

**Table 5 Factor analysis results with VARIMAX rotation of the Six Proxies of Industry-level Characteristics**

Resource Configuration	Indicator	Factor Loading	Eigenvalue	Variance Explained	Cumulative Variance
<b>Factor1</b> Industry Information Value	ILN	0.860	2.155	35.909	35.909
	CI	0.729			
	HI	-0.712			
	FSI	0.578			
<b>Factor2</b> Industry Government Economic Incentives	IEI	0.845	1.113	18.547	54.456
<b>Factor3</b> Industry Information Homogeneity	IH	0.945	1.044	17.399	71.855
Kaiser-Meyer-Olkin Measure of Sampling Adequacy				0.667	
		Approx. Chi-Square		5098.508	
Bartlett's Test of Sphericity		df		15	
		Sig.		0.000	

Notes: *ACCY* represents the accuracy in analysts' earnings forecasts and is defined as the negative of the absolute difference between the forecast and actual earnings, scaled by price; *CI* is the proxy of the common information and defined as news released by one industry member that can be similarly applied to other industry members; *ILN* is the proxy of the industry-level news and defined as the industry-level earnings surprise; *FSI* is the proxy of the firm-specific information and measured by the percentage of industry members in a year with R&D expenses; *IH* is the proxy of the industry homogeneity and defined as the industry associated primarily with common information; *HI* represents the degree of the industry concentration; *IEI* is the dummy variable that takes the value of 1 (0) if the firm is affiliated with economic incentives (non- economic incentives) industry; *SIZE* is defined as the logarithm of total assets of firm; *Z* represents the financial distress score; *STDROE* represents the standard deviation of earnings over the previous two years; *NUMEST* is the proxy of the number of analysts following; *SURPRISE* represents the absolute value of the earnings surprise; *LOSS* is the dummy variable that takes the value of 1 (0) if firm-year observations have positive (negative) earnings; *EPS* represents the earnings per share excluding extraordinary items.

**Table 6 Multivariate Tests on the Association between Industry-level Characteristics and Forecast Accuracy**

$$ACCY_t = \alpha_0 + \alpha_1 Factor1 + \alpha_2 Factor2 + \alpha_3 Factor3 + \alpha_4 SIZE + \alpha_5 Z + \alpha_6 STDROE + \alpha_7 NUMEST + \alpha_8 SURPRISE + \alpha_9 LOSS + \alpha_{10} EPS + \varepsilon$$

	Expected Sign	(1)	(2)	(3)	(4)
Intercept		-0.0682 (-9.680)***	-0.0706 (-10.060)***	-0.0305 (-12.599)***	-0.0693 (-9.844)***
<i>Factor1</i>	+	0.0034 (2.421)***			0.0035 (2.530)***
<i>Factor2</i>	+		0.0042 (3.098)***		0.0044 (3.205)***
<i>Factor3</i>	+			0.0004 (0.763)	0.0021 (1.524)
<i>SIZE</i>	+	0.0011 (2.689)***	0.0011 (2.245)**	0.0011 (2.775)***	0.0011 (2.779)***
<i>Z</i>	+	0.0004 (7.461)***	0.0004 (5.940)***	0.0004 (8.084)***	0.0004 (7.126)***
<i>STDROE</i>	—	-0.00001 (-1.436)	-0.00001 (-1.811)*	-0.00001 (-1.257)	-0.00001 (-1.402)
<i>NUMEST</i>	+	0.0005 (6.433)***	0.0005 (8.117)***	0.0005 (6.522)***	0.0005 (6.358)***
<i>SURPRISE</i>	—	-0.0001 (-2.305)**	-0.00001 (-2.460)**	-0.0001 (-2.292)**	-0.0001 (-2.342)**
<i>LOSS</i>	—	-0.0270 (-15.483)***	-0.0263 (-15.337)***	-0.0261 (-15.074)***	-0.0269 (-15.293)***
<i>EPS</i>	—	0.0035 (8.233)***	0.0300 (8.126)***	0.0034 (8.087)***	0.0035 (8.244)***
Adj. $R^2$		13.67%	13.74%	13.62%	13.87%
<i>F-test</i>		86.117	85.522	85.423	81.917

Notes: *Factor1* represents the dimension of industry information value, and including *ILN*, *CI*, *HI* as well as *FSI*; *Factor 2* represents the dimension of government economic incentives, and including *IEI*; *Factor 3* represents the dimension of industry information homogeneity, and including *IH*; *SIZE* is defined as the logarithm of total assets of firm; *Z* represents the financial distress score; *STDROE* represents the standard deviation of earnings over the previous two years; *NUMEST* is the proxy of the number of analysts following; *SURPRISE* represents the absolute value of the earnings surprise; *LOSS* is the dummy variable that takes the value of 1 (0) if firm-year observations have positive (negative) earnings; *EPS* represents the earnings per share excluding extraordinary items. \*\*\*, \*\*, \* indicate significance at 1%, 5%, and 10% percent levels in a two-tailed test, respectively. All the t-statistics are based on White's (1980) heteroscedasticity-corrected standard errors by each firm. t-statistic are noted in parentheses below each coefficient estimate.

## 5. CONCLUDING REMARKS

An analyst processes, transforms, and integrates a company's public and private information and is thus a significant "information mediator" in the capital market. An analyst functions to guide the information flow in the capital market, and an analyst's recommendation supplementary to the company's information. Through the analysis of analysts' behavior, we can infer the beliefs of investors that are not directly observable. The findings of this study show that free competition will stimulate the innovation of product and knowledge among enterprises. The enterprise signaling differentiating information in order to establish a position of competitiveness in turn assists the promotion of the industry's information transparency, thereby granting analysts the access to sufficient and high-quality information which in turn results in higher accuracy in their earnings forecasts. Moreover, different from the competitive mechanism of the market, the involvement of government regulation will change the rules and cause blockages to free competition. However, since industries provided with government economic incentives have higher entry barriers and protective policies, these monopolizing enterprises are able to operate steadily and enjoy the most innovative profits under a certain set rules while facing a less competitive industry environment. Hence, relatively low uncertainty of industrial information environment and high policy transparency will help to raise the accuracy of the earnings forecasts. Finally, information transfer effect will affect the demand for information within the industry and the demand-supply relationship, and further determines the information transparency. Higher common information and industry-level news within an industry raises the accuracy of analysts' earnings forecasts. However, the firm-specific information and industry homogeneity do not have a significant influence. Overall, the result shows that the higher information transparency there is within an industry, the more accurate analysts' earnings forecasts will be. This can also increase the demand for analysts' reports in the market. Thus, while endeavoring to promote the governance of information transparency, the competent authorities should also focus on how to reinforce industry-level transparency.

## REFERENCES

- Aerts, W., D. Cormier and M. Magnan. 2008. Corporate Environmental Disclosure, Financial Markets and the Media: an International Perspective. *Ecological Economics* 64 (3): 643-659.
- Altman, E. 1968. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *Journal of Finance* 23 (4): 589-609.
- Baron, D. 2000. *Business and its Environment (3rd ed.)*. Upper Saddle River, NJ: Prentice Hall.
- Barron, O. E., D. Byard, C. Kile and E. J. Riedl. 2002. High-Technology Intangibles and Analysts' Forecasts. *Journal of Accounting* 40(2): 289-312.
- Beckers, S., M. Steliaros and A. Thomson. 2004. Bias in European Analysts' Earnings Forecast. *Financial Analysts Journal* 60 (2): 74-85.
- Bonsall IV, S. B., Z. Bozanic and P. Fischer. 2013. What Do Management Earnings Forecasts Convey About the Macroeconomy? *Journal of Accounting Research* (first published online: 9 MAR 2013):1-42.
- Breyer, S. 1990. Regulation and Deregulation in the United States: Airlines, Telecommunications and Antitrust. In *Giandomenico Majone, ed. Deregulation or Re-regulation? Regulatory Reform in Europe and the United States*, New York, St. Martin's Press.
- Cairney, T. D. and C. Pantzalis. 2002. An Empirical Examination of the Determinants of Industry-Level Earnings Forecast Disclosure Frequency. *American Business Review* 20 (1): 123-132.
- Clinch, G. and N. Sinclair. 1987. Intra-Industry Information Releases: A Recursive Systems Approach. *Journal of Accounting and Economics* 9 (1): 89-106.
- Cready, W. M. and U. G. Gurun, 2010. Aggregate Market Reaction to Earnings Announcements. *Journal of Accounting Research* (Supplement 2010): 289-334.
- Eames, M. J. and S. M. Glover. 2003. Earnings Predictability and the Direction of Analysts' Earnings Forecast Errors. *The Accounting Review* 78 (3): 707-724.
- Firth, M. 1976. The Impact of Earnings Announcements on the Share Price Behavior of Similar Type Firms. *Economic Journal* 86 (342): 296-306.



- Foster, G. 1981. Intra-Industry Information Transfers Associated with Earnings Releases. *Journal of Accounting and Economics* 3 (3): 201-232.
- Freeman, R. and S. Tse. 1992. An Earnings Prediction Approach to Examining Inter-Company Information Transfer. *Journal of Accounting and Economics* 15: 509-523.
- Gallego-Álvarez, I., I. M. García-Sánchez and L. Rodríguez-Domínguez. 2008. Voluntary and Compulsory Information Disclosed Online: Effect of Industry Concentration and Other Explanatory Factors the Presentation of Financial Information at Corporate Web Sites. *Online Information Review* 32 (5): 596-622.
- Geroski, P. A. 1990. Innovation, Technological Opportunity, and Market Structure. *Oxford Economic Papers* 42(3): 586-602.
- Greer, D. F. 1987. *Business, Government, and Society*. New York, MacMillian Publishing Company.
- Gu, F. and W. Wang. 2005. Intangible Assets, Information Complexity, and Analysts' Earnings Forecasts. *Journal of Business Finance & Accounting* 32(9-10): 1673-1702.
- Han, J. and J. Wild. 1990. Unexpected Earnings and Intraindustry Information Transfers: Further Evidence. *Journal of Accounting Research*, 28 (1): 211-219.
- Hong, H. and J. Kubik. 2003. Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts. *The Journal of Finance* 58 (1): 313-351.
- Howe, J. S., E. Unlu and X. M. Yan. 2009. The Predictive Content of Aggregate Analyst Recommendations. *Journal of Accounting Research* 47 (3): 799-821.
- Hwang, L., C. L. Jan and S. Basu. 1996. Loss Firms and Analysts' Earnings Forecast Errors. *Journal of Financial Statement Analysis* 1 (2): 18-30.
- Keane, M. P. and D. E. Runkle. 1998. Are Financial Analysts' Forecasts of Corporate Profits Rational? *Journal of Political Economy* 106 (4): 768-805.
- King, R., G. Pownall and G. Waymire. 1990. Expectations Adjustment via Timely Management Forecasts: Review, Synthesis, and Suggestions for Future Research. *Journal of Accounting Literature* 9: 113-44.
- Kridel, D. J., D. E. M. Sappington and D. L. Weisman. 1996. The Effects of

- Incentive Regulation in the Telecommunications Industry: A Survey. *Journal of Regulatory Economics* 9 (3): 269-306.
- Kross, W., B. Ro and D. Schroeder. 1990. Earnings Expectations: the Analysts' Information Advantage. *The Accounting Review* 65 (2): 461-476.
- Lang, M. and R. Lundholm. 1996. Corporate Disclosure Policy and Analyst Behavior. *The Accounting Review* 71: 467-492.
- Mahon, J. and E. Murray. 1981. Strategic Planning for Regulated Companies. *Strategic Management Journal* 2: 251-262.
- Marsh, S. 1998. Creating Barriers for Foreign Competitors: A Study of the Impact of Anti-Dumping Actions on the Performance of US Firms. *Strategic Management Journal* 19: 25-37.
- Michaely, R. and K. L. Womack. 1999. Conflict of Interest and the Credibility of Underwriter Analyst Recommendations. *Review of Financial Studies* 12: 653-686.
- Miller, G. 2002. Earnings Performance and Discretionary Disclosure. *Journal of Accounting Research* 40 (1): 173-204.
- Moyer, R. C., R. E. Chatfield and P. M. Sisneros. 1989. Security Analyst Monitoring Activity: Agency Costs and Information Demands. *Journal of Financial and Quantitative Analysis* 24 (4): 503-512.
- Schipper, K. 1990. Commentary: Information Transfers. *Accounting Horizons* 4 (4): 97-107.
- Schumpeter, J. A. 1976. *Capitalism, Socialism and Democracy*. Harper and Row, New York, NY.
- Shaffer, B. 1995. Firm Level Responses to Government Regulation: Theory and Research Approaches. *Journal of Management* 21: 495-514.
- Shivakumar, L. 2010. Discussion of Aggregate Market Reaction to Earnings Announcements. *Journal of Accounting Research* 48: 335-42.
- Simon, M. and C. K. Shallone. 2013. Effects of Firm Size and Market Structures in Technological Innovation: A Review of Literature. *Journal of Sustainable Development* 2(2): 170-181.

- Stickel, S. 1992. Reputation and Performance among Security Analysts. *Journal of Finance* 47: 1811-1836.
- White, H. 1980. A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica* 48 (4): 817-838.
- Womack, K. 1996. Do Brokerage Analysts' Recommendations have Investment Value? *Journal of Finance* 51: 137-167.
- Yu, M. 2010. Analyst Forecast Properties, Analyst Following and Governance Disclosures: A Global Perspective. *Journal of International Accounting, Auditing and Taxation* 19 (1): 1-15.