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Management Earnings Forecasts Information Transfers between Related Industries: Evidence from Taiwan

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摘要

本研究主要探討管理當局盈餘預測是否於上、下游關聯產業間存在資訊移轉之現象。以民國八十六年至九十三年國內上市公司進行研究，相較於之前的研究發現資訊移轉僅侷限於相同產業，本研究之實證結果顯示，公司宣告盈餘預測時，確實會對其關聯產業形成資訊移轉現象。此外，本研究亦發現產業關聯程度與消息型態會影響資訊移轉程度。整體而言，不論是好消息或壞消息，均產生資訊移轉現象；而壞消息宣告的資訊移轉程度大於好消息。若從產業關聯程度高低分析，不論是在好消息或壞消息的組別，資訊移轉的強度皆與產業關聯程度呈正相關。因此，本文彌補相關文獻之不足，提供影響跨產業資訊移轉之因素的研究證據，可供相關學術與實務參考。

【關鍵字】資訊移轉、管理當局盈餘預測、關聯產業

Abstract

Using *Data Bank of Taiwan Economic Journal* for the eight-year period January 1997 through December 2004, we empirically evaluate information transfers conveyed by the management earnings forecast to the related industries. Contrary to earlier findings in the literature, we find information transfers across industries with input-output relationships during the release of earnings forecasts. We find the strength of information transfers are impacted by the news type (good news v.s. bad news) and that greater information transfers are conveyed in the bad news group. Our results also indicate that the higher the degree of relatedness between industries, the more information transfers are conveyed, whether the news type is good or bad. Thus, we contribute to the information transfer literature by identifying the characteristics that affect information transfers across related industries.

【Keywords】information transfers, management earnings forecasts, related industries

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1. Introduction

Information transfers have been documented in various settings including earnings announcements (Foster, 1981; Freeman & Tse, 1992; Asthana & Mishra, 2001), sales announcements (Olsen & Dietrich, 1985), and management earnings forecasts (Baginski, 1987; Clinch & Sinclair, 1987; Han, Wild, & Ramesh, 1989). When an information disclosure by one firm affects the stock price of another firm an externality is created. We consider information transfers when a firm's voluntary management earnings forecasts affect the equity valuation of other firms. Reasons to focus on management earnings forecasts instead of earnings announcements or other information are voluntary forecasts provide more timeliness and relevant information before earnings announcements and can be precisely measured and easily verified (Healy & Palepu, 2001).

Earlier research in this context provided mixed findings. For instance, Han et al. (1989) find that voluntarily disclosed earnings forecasts are associated with abnormal returns for both forecast firms and other firms in the same industry. However, they do not find significant information transfers after adjusting for the industry cross-sectional co-variation in returns. This suggests that while management earnings forecasts may have firm specific information they have little information for other firms in the industry beyond what can be ascribed to industry-wide commonalities. Thus, for management earnings forecasts there is scant evidence of announcing firm's forecasts affecting the valuation of other firms in the industry in the context of management earnings forecasts.

In contrast, we posit that management earnings forecasts have the potential to affect the valuation of firms in other industries due to firm and/or industry specific information in the forecasts. This is likely to happen when there is interdependence or linkage between two industries, such as that exists between two industries when output of one industry becomes the input for another industry. We also hypothesize that the magnitude of such information transfers are dependent on the strength of the linkage between the announcing and non-announcing firms.

Though the existence of information transfers has been documented in various settings ours is the first study of how information transfers around management earnings forecasts are affected by interdependencies between industries. Olsen and Dietrich (1985) also investigate inter-industry information transfers. They find evidence of vertical information transfers from "Retailers" to "Suppliers" during monthly sales announcements by retailers that lead to statistically significant changes in stock prices of both the retailers and the suppliers. In their research, they only consider information transfer from retailer to its suppliers and other firms in industries that supply the retail industry. We argue that similar vertical information transfers can occur between the upstream and downstream industries. Hence, we expand the idea of Olsen and Dietrich (1985) and refer to Fan and Lang (2000) to measure the degree of inter-industry relatedness, then examining whether the information transfer exists in related industries. Comparing with the Olsen and Dietrich (1985) where more focus are put on the firm-level information transfers form "Retailers" to "Suppliers", we provide more insight of information transfers among all related industries.

Such information transfers are likely to grow in frequency and magnitude with the improved integration of supply chains. With the rapid advance of Enterprise Resource Planning (ERP), Customer Relationship Management (CRM) and other supply chain management technologies we have seen a seamless integration of firms in the value chain that links raw material providers, manufacturers, distributors and marketers. Leading companies such as DuPont, Hewlett-Packard, Procter and Gamble and 3M have used supply chain management to improve their competitive position (Davis, 1993; Cooper & Ellram, 1993; Cottril, 1997; Keebler, Manrodt, Durtsch, & Ledyard, 1999). Probably the most compelling story of our time is the Wal-Mart that has revolutionized the whole retail industry by effective supply chain management. Wal-Mart, for example, derived a competitive advantage from their exclusive collaborations and from the proprietary sharing of information with their suppliers and partners such as Proctor & Gamble (Agrawal & Pak, 2001). Firms that are linked in a supply chain share resources and information, eliminate duplications, and thereby enable rapid information flow that ultimately results in a smooth product flow. This use of common information resources for planning, production and delivery processes creates interdependence among the firms

This seamless integration of supply chains has prevailed in practice and greatly intensifies the interdependence between related industries having input-output relationship, which lies at the core of the inter-industry information transfers. Thus, investors can potentially use information about any firm in both upstream and downstream industries to revise their beliefs about the performance of the other firms in the related industries. Given that supply chain management is still rapidly evolving, the affect of input-output relations between related industries on inter-industry information transfers is likely to grow in importance. However, there is little extant empirical research on inter-industry information transfers related to such relationships.

In this paper, we investigate information transfers due to management earnings forecasts among firms having input-output relationships between related industries. We find information transfers across industries due to management earnings forecasts even after controlling for industry effects. In addition, we document that characteristics of dependence such as degree of relatedness and the type of news, good vs. bad, affect the magnitude of information transfers. The results show greater information transfers in bad news group. We also find that the higher degree of relatedness across the industries, the more information transfers occurs regardless the type of information. In addition and contrary to Han et al. (1989), we find information transfers after controlling for industry effects using a two-index pricing model.

The rest of the paper is organized as follows. Section 2 develops our research hypotheses related to information transfers due to management earnings forecasts and its dependence on the strength of industry interdependence. Section 3 describes criteria for sample selection and research methodology. Section 4 presents and discusses the empirical results. In section 5, we conclude the paper with a brief summary.

2. Development of Research Hypotheses

Inter-company information transfers happen when market participants use the information released by firm $i \in S_f$, the set of forecasting firms, to make inferences about the security return behavior of firm $j \in S_n$, the set of non-forecasting firms.[1] We investigate the association between the market reaction to a firm's management earnings forecast and the stock price change of other firms in the related industries. Fan and Lang (2000) indicate that two industries are vertically related if one can employ the other's products or services as input for its own production or supply output as the other's input. Firms in related industries have correlated fundamentals by their interaction with each other either through their trading relationship or through market prices for their inputs and outputs. They may also face relatively similar demand and/or technological shocks (Menzly & Ozbas, 2007). Besides, supply chain integrations also lead to interdependence in input and output of the firms in the related industries. Firms in a supply chain can use any combination of information integration, financial integration and operational integration. In information integration partners use common information for decision making such as resources planning, production and delivery processes. Financial integration results in change in terms and conditions of payment, for example a manufacturer may accept payment at the time the retailer sells its product rather than when the manufacturer delivers the product to the

1 Schipper (1990) provides a detailed discussion on information transfers.

retailer. Operational integration allows sharing of human and physical resources between partners in the supply chain. For example, a manufacturer may provide floor space within its plant to suppliers to produce components for the assembly line in Just In Time (JIT) implementations.

Hence, any economic shock to one firm can potentially ripple through other firms in the related industries. For example, a demand slowdown or growth at the retailer can lead to demand slowdown or growth for the supplier and possibly for other firms similar to the supplier in the supplier's industry. Thus, information about retailer's revenue or earnings can be used to revise the belief about a supplier's revenue or earnings and to adjust the supplier's equity valuation. In a seminal article, Olsen and Dietrich (1985) provide evidence of such vertical information transfers from "Retailers" to "Suppliers." They show that monthly sales announcements by retailers, lead to statistically significant changes in stock prices of both retailers and their suppliers. We argue that similar vertical information transfers can occur between firms in related industries with input-output relationship. In keeping with the above arguments and earlier research, we formally state our first hypothesis in the null form as follows.

$$H1_0:\ E\langle \omega_J \,|\, \phi_i \rangle = 0,\ for\ all\ \ j \in S_n\ \ and\ \ i \in S_f\ ,$$
$$H1\ :\ E\langle \omega_J \,|\, \phi_i \rangle \neq 0,\ for\ all\ \ j \in S_n\ \ and\ \ i \in S_f\ ,$$

where ω_j is a non-directional measure of abnormal return activity based on announcement period excess returns, ϕ_i is the management earnings forecasts by firm *i* and *j* is a non-forecasting firm in a related industry. As defined earlier, S_f and S_n are sets of forecasting and non-forecasting firms. Related industries defined in this paper is based on input-output relationship as reported in Tables of related industries published by the Executive Yuan of Taiwan Government. Detailed computation of the degree of relatedness is provided in section III.

Contingent on rejection of the null hypothesis one can further hypothesize a directional relationship between the forecasting and non-forecasting firms. We expect that there is a positive information transfer arising from the interdependence and cooperation among firms in related industries. First, due to the linkage between related industries the changes in demand for downstream industry will also affect the demand for upstream industry. For example, investors can revise their assessment of the profitability of automobile parts based on demand information for automobiles. Second, to get the most out of supply chain management, firms in the supply chain must align their business strategies with the overall supply chain strategy. Attention is directed to integrating the firm's business process with its partner's business processes to reduce supply chain operating costs, which generally requires long-term focus and cooperation from other partners in the supply chain. For example, Dell requires its suppliers to provide inventories within approximately 15 minutes from its manufacturing plants since it carries very little work in process inventory. Dell works out a win-win situation with the suppliers by assuring them a large volume of its business and sourcing with few suppliers only. Therefore, the relationship in a supply chain is cooperative rather than competitive, and we expect good (bad) news for one partner is good (bad) news for others. For example, bad news for Sears is bad news for the suppliers of Sears. Since firms in related industries are interdependent and co-operative in nature we hypothesize that there is a positive relation between the abnormal returns of forecasting and non-forecasting firms. This leads to our second hypothesis:

$H2_0$: $E(\eta_j \mid \mu_i > 0) \le 0$, and $E(\eta_j \mid \mu_i < 0) \ge 0$ for all $j \in_n$ and $i \in_f$,

$H2_a$: $E(\eta_j \mid \mu_i > 0) > 0$, and $E(\eta_j \mid \mu_i < 0) < 0$ for all $j \in_n$ and $i \in_f$,

where $\mu_i = E(\eta_i \mid \phi_i)$ and η_j is a directional measure of abnormal return activity during the event period and the rest of variables are as defined before.

Next, we consider the degree of vertical relatedness between two industries. Modern industrial production involves a series of sequential processing by different parts of the value chain. Different industries may serve as input suppliers to each other and one industry's output could be sold as an intermediate product to several other industries. Industry with a relatively larger proportion of outputs to his downstream industry or demand with a relatively larger proportion inputs from his upstream industry display greater interdependence between the two industries. As a consequence earnings forecasts by a highly related firm should convey more information about the earnings of other firms that are closely connected with the forecasts firm. Accordingly, our final hypothesis deals with the degree of relatedness among industries. This hypothesis may be stated formally as:

H_{30}:: $E(\eta_j \mid \phi_i, high-vert) \le E(\eta_j \mid \phi_i, low-vert)$, $for\ all$ $j \in_n$ and $i \in_f$,

H_{3a}: $E(\eta_j \mid \phi_i, high-vert) > E(\eta_j \mid \phi_i, low-vert)$, $for\ all$ $j \in_n$ and $i \in_f$,

Where *high-vert* denotes firms in high vertically related firms industries and low-vert denotes firms in weak vertically related industries.

3. Research Methodology

3.1 Sample Selection

Managers' forecasts of annual earnings are obtained from the Data Bank of Taiwan

Economic Journal for the eight-year period from January 1997 through December 2004. To be included in the sample, the firm must: (1) be listed on the Taiwan Stock Exchange with calendar fiscal year, (2) not be in the financing and miscellaneous industries, (3) be in an industry that has noticeable upstream and/or downstream industries; namely, the sampled industry accounts for at least 1 percent of the output (input) of its upstream (downstream) industries, and (4) not have changed its major business during the examination period. Also, managers' earnings forecasts must: (1) be directly attributed to a company official, (2) be in the form of a point estimate or specified range (in which case the midpoint is taken), and (3) be the first voluntary disclosure of the firm and the industry in which the firm operates. These selection procedures yield 94 management earnings forecasts in 12 industries[2]. All other firms in the upstream and/or downstream industries of the forecasting firms not releasing preliminary earnings announcements or earnings forecasts within two trading days of forecasting firms are considered non- forecasting firms. Non-forecasting firms are eliminated from the sample if (1) daily returns are unavailable from the Data Bank of Taiwan Economic Journal, and (2) insufficient returns exist for computing abnormal returns. After considering these criteria, there are 7,075 non-forecasting firms in our sample. 545 non-forecasting firms with other firms in related industries are eliminated simultaneously announcing their management earnings forecast during the event period of forecasting firms. 644 observations are excluded from our sample because of confounding information released such as material price increases, dividend payment, prior year earnings announcement ...etc., that could cause stock price during the event period. Finally, we delete the 64 outliers that are over or below 3 times standard deviation. These selection procedures yield 5,642 non-forecasting observations in our final sample.

3.2 Measurement of Variable

3.2.1 Abnormal Stock Returns

We use abnormal returns to examine information transfers for two reasons: (1) analyst earnings forecasts in Taiwan have not been widely tested (Lee, 2000), and may not be representative of investor's expectations, and (2) Han and Wild (1990) suggest that using forecasting firms' unsystematic stock returns as a proxy for the financial reporting signal may not significantly affect the inferences drawn because similar results are obtained using

2 There should be 96 management earnings forecasts in 12 industries in 8 years. 2 forecast announcing firms are excluded from our sample because of insufficient returns exist for computing abnormal returns in estimated period.

unexpected earnings and has been extensively used in information transfers literature.

Estimates of abnormal stock returns for forecasting and non-forecasting firms at earnings forecast dates are obtained using the following market model:

$$AR_{i,t} = R_{i,t} - \left(\hat{\alpha}_i + \hat{\beta}_i R_{M,t}\right) \tag{1}$$

where $R_{j,t}$ is the daily stock return for firm *i* on day *t*, and $R_{M,t}$ is the return for value-weighted market index on day *t*. The model's parameters, α_i and β_i are estimated using *OLS*; the estimation period extends from the preceding three hundred trading days through three trading days prior to the earnings forecast date.

Two measures of abnormal return activities in our paper are standardized cumulative price variance (SCVR) and standardized cumulative abnormal returns (SCAR). SCVR is used to measure non-directional abnormal returns. Previous studies (Foster, 1981; Han et al., 1989) suggested that earnings information released by one firm might convey positive information to some firms but negative information to others in the same industry, which may result in offsetting overall market reactions. To avoid such situation, we employed SCVR to test our hypothesis H1.

The SCVR metric, similar to the one in Han et al. (1989), is computed for firm *i*, where (t_1, t_2) denotes the event period from day t_1 to day t_2. $AR_{i,t}$ is the residual form equation (1), $\omega^2_{i,(t_1,t_2)}$ is an estimate of var $\left(\sum_{t=t_1}^{t_2} AR_{i,t}\right)$.

$$\mathrm{SCVR}_{i,(t_1,t_2)} = \left(\sum_{t=t_1}^{t_2} \mathrm{AR}_{i,t}\right)^2 \Big/ \left(\omega^2_{i,(t_1,t_2)}\right) \tag{2}$$

SCAR is used to measure the directional abnormal return activity (Patell, 1976; Foster, 1981; Han et al., 1989). The measure could test whether a release by a firm that has a favorable (unfavorable) impact on its own stock prices also has a similar impact on the stock prices of other firms in related industries. It could provide more information than SCVR on the direction and magnitude of price changes.

The SCAR metric is computed as follows:

$$SCAR_{i,\ t_1,t_2)} = \sum_{t=t_1}^{t_2} SAR_{i,t} \tag{3}$$

where $SAR_{i,t}$ is the standardized abnormal return of firm i in the event period from t_1 to t_2.

3.2.2 Vertical Relatedness Index

Fan and Lang (2000) construct an interindustry relatedness index similar to Lemelin (1982) by using the input-output (IO) table prepared by the Bureau of Economic Analysis to describe the commodity flows in the U.S. We apply their vertical relatedness index to measure the level of interdependence between two industries using Transactions Table at Producers' Prices in Taiwan (2001) released by the Directorate-General of Budget, Accounting and Statistics, Executive Yuan, R.O.C. The table is a matrix containing dollar value of commodity flows between each pair of roughly 49 private-sector, intermediate IO industries. The content of the table reports for each pair of industries, *i* and *j*, the dollar value of *i*'s output required to produce industry *j*'s total output, denoted as a_{ij}.

To calculate the vertical relatedness index (VRI) between industry *i* and *j* (V_{ij}), we take the average of a_{ij} and a_{ji} on an unit-dollar basis.

Table 1 Industry-level vertical relatedness: An illustration on the plastics industry (*i*)

Industry *j*	Chemical	Textile	Biotechnology
Plastics used by industry *j*; a_{ij}	1,028	43,678	13,228*
Total output of industry *j*; Q_j	769,995	165,618	255,169*
Ratio of industry of plastics used total *j* output ; $v_{ij} = a_{ij}/Q_j$	0.001	0.264	0.052
Industry *j*'s output used by the plastics industry; a_{ij}	306,398	0	8,030*
Total output of plastics; Q_i	468,619	468,619	468,619*
Ratio of *j* industry used total plastics output; $v_{ji} = a_{ji}/Q_i$	0.653	0.000	0.017
Vertical relatedness index between plastics and the *j*th industries; $V_{ij} = 1/2\ (v_{ij} + v_{ji})$	0.33	0.13	0.03

Source: Transactions Table at Producers' Prices of Taiwan (year 2001) prepared by the Directorate-General of Budget, Accounting and Statistics, Executive Yuan, R.O.C.
*: In millions of New Taiwan dollars

Table 1 provides three examples to explain the way to measure the vertical relatedness. For instance, the total output of plastics (Q_i) was NT$ 468, 619 million and total output of chemical (Q_j) was NT$ 769,995 million. The chemical industry consumed NT$ 1,028 million of plastics (a_{ij}), whereas the plastics industry consumed NT$ 306, 398 million of chemical (a_{ji}) as input. On an unit-dollar basis, the chemical industry consumed NT$ 0.001 (1,028/769,995) of plastics for each dollar of chemical produced (v_{ij}), whereas the plastics industry consumed NT$ 0.653 of chemical for each dollar of plastics produced (v_{ji}). The vertical relatedness between the two industries is 0.33 (V_{ij} = 1/2 ($v_{ij}+v_{ji}$)= 1/2 (0.001+0.653)), which indicates the average input transfers between the two industries. All the vertical relatedness index that are greater or equal to 0.01 are induced in our sample.

3.3 Model

To test the hypothesis H1a, we specify the model for the non-directional test as follows:

$$SCVR(NF) = \alpha_0 + \alpha_0 SCVR(F) + \varepsilon_0 \tag{4}$$

SCVR (NF): standardized cumulative price variance over the event window of (-1,1) of non-forecasting firms.

SCVR (F): standardized cumulative price variance over the event window of (-1,1) of forecasting firms.

To test the hypothesis H2, we specify the model for the directional test as follows:

$$SCAR(NF) = \beta_0 + \beta_1 SCAR(F) + \varepsilon_0 \tag{5}$$

SCVR (NF): standardized cumulative abnormal returns over the event window of (-1,1) of non-forecasting firms.

SCVR (F): standardized cumulative abnormal returns over the event window of (-1,1) of forecasting firms.

To test the hypothesis H3, we set the model as follows:

$$SCAR(NF) = \beta_0 + \beta_1 SCAR(F) + \beta_2 VRI \quad SCAR(F) + \varepsilon_0 \tag{6}$$

VRI: Vertical relatedness index between two related industries.

4. Empirical Results and Discussion

Table 2 provides descriptive statistics of the market values for the forecasting and non-forecasting firms in each industry. The forecasting firms' mean capitalization values range from NT$ 2,790 millions to NT$ 104,808 millions while those for non-forecasting firms range from NT$ 4,150 millions to NT$ 45,427 millions. The number of non-forecasting firms in each industry ranges from 31 to 306. The average sizes of forecasting firms are greater than those of the non-forecasting firms in general. That is, large firms are more likely to release earnings forecasts than others.

Table 2 Distribution of market values of forecasting and non-forecasting firms (millions of NT dollars)

	Forecasting firms				Non-forecasting firms in the same industries			
Industry	Obs.	Mean	Median	Standard Deviation	Obs.	Mean	Median	Standard Deviation
Food	7	2,790	2,448	1,141	115	6,107	1,994	14,058
Paper	8	7,615	5,656	6,739	56	7,655	6,651	5,906
Chemical	8	3,664	1,839	3,359	113	4,288	2,539	4,856
Textile	7	16,316	10,106	23,279	132	8,549	2,313	22,919
Plastic	8	104,808	5,784	135,585	88	45,427	8,659	85,466
Biotechnology	8	5,088	3,610	4,334	133	4,059	1,636	5,681
Cement	8	17,119	7,260	16,075	56	16,511	6,088	19,189
Steel	8	5,360	4,879	4,600	200	12,246	2,934	41,906
Appliances & Cable	8	4,730	1,222	3,199	237	4,348	2,264	7,654
Automobile	8	34,332	1,170	18,984	31	35,013	33,987	23,636
Construction	8	5,086	919	7,919	306	4,150	1,753	6,524
Transportation	8	19,342	4,631	20,811	151	13,379	4,275	18,029
Total	94	19,353	4,800	50,217	1,618	9,930	2,879	29,017

Table 3 Distribution of SCVR (-1,1) of forecasting and non-forecasting firms in related industries

	Forecasting firms				Non-forecasting firms in the same industries			
Industry	Obs.	Mean	Median	Standard Deviation	Obs.	Mean	Median	Standard Deviation
Food	7	2.99	0.66	5.71	149	5.01	5,41	5.10
Paper	8	2.87	0.78	5.78	500	3.63	3.07	2.13
Chemical	8	3.33	0.78	6.31	264	1.87	0.41	2.68
Textile	7	2.80	0.72	5.19	121	3.27	1.53	4.32
Plastic	8	3.41	1.03	5.95	531	7.79	0.94	11.14
Biotechnology	8	4.15	1.23	7.12	670	1.14	1.78	1.01
Cement	8	4.61	1.02	8.0e	707	3.10	0.96	4.33
Steel	8	4.05	0.97	7.43	544	7.90	5.33	8.45
Appliances & Cable	8	2.48	0.77	4.26	359	4.1	0.45	4.97
Automobile	8	4.52	1.26	7.78	551	2.15	1.43	2.55
Construction	8	3.31	0.98	5.94	659	4.57	3.24	4.97
Transportation	8	4.31	0.91	7.43	383	0.97	0.6	0.98
Total	94	3.74	0.98	6.78	5,438	3.84	1.78	5.86

SCVR (-1,1): standardized cumulative price variance over the event window of (-1,1).

Table 3 provides the mean, median and standard deviation of *SCVR* for forecasting and non-forecasting firms in the related industries. The average SCVR of non-forecasting firms are greater than one in all industries except the transportation industry in our sample. It suggests that information transfers seem to exist in most of the industries.

Table 4 Non-directional information transfers

Panel A: Non-directional abnormal return behavior				
		Forecasting firms		Non-forecasting firms
SCVR		3.84***		3.74***
Panel B: Regressions of non-forecasting firms' SCVR on forecasting firms' SCVR				
	N	α_0	α_1	Adj.R^2
Individual (i)	5,438	3.325***	0.11***	0.01
*(**/***) designates 10% (5%/1%) significance level, two-tailed tests.				

SCVR (-1,1): standardized cumulative price variance over the event window of (-1,1).

Table 4 provides the empirical results for our first hypothesis. The mean *SCVR* for days (-1, 1) is 3.84 for forecasting firms and is significant at 1% level. Similarly, the mean *SCVR* for the non-forecasting firms are 3.74 and is significant at 1% level. The regression results of relating non-forecasting firms' SCVR to forecasting firms' SCVR are reported in Panel B of Table 4. The coefficient estimate of α_1 is significantly positive, indicating a positive association between forecasting and non-forecasting firms' *SCVR*.

Table 5 Information transfers by industries

Model / Sample	$SCAR(NF) = \beta_0 + \beta_1 SCAR(F) + \varepsilon$				
	β_0	$t(\beta_0)$	β_1	$T(\beta_1)$	R^2
All	0.073	2.66***	0.245	17.45***	0.06
Food	0.039	0.15	0.026	0.25	0.002
Paper	0.276	3.2***	0.397	8.42***	0.17
Chemical	0.626	4.75***	0.433	5.68***	0.10
Textile	-0.454	-3.1***	0.447	6.23***	0.25
Plastic	0.314	3.38***	0.154	4.36***	0.04
Biotechnology	0.509	6.42***	0.279	4.9***	0.03
Cement	-0.26	-3.74***	0.432	9.7***	0.15
Steel	-0.078	-0.8	0.184	5.06***	0.05
Appliances & Cable	0.156	1.61	0.095	2.19**	0.01
Automobile	0.359	4.04***	0.447	8.48***	0.13
Construction	0.011	0.12	0.106	2.98***	0.01
Transportation	0.243	2.31**	0.435	4.19***	0.05

$SCAR_j$: standardized cumulative abnormal returns (%).
*(**/***) designates 10% (5%/1%) significance level, two-tailed tests.

Since the null hypothesis H_{10} is rejected, we then performed regression analysis in order to further investigate the directional relationship of information transfers between the forecasting and non-forecasting firms. In Table 5, we reported the results for the total sample as well as for each industry. The coefficient β_1 in model (5) is significantly positive at 1% level for the total sample and it is also statistically significant in 11 out of the 12 industries. Therefore, consistent with Olsen and Detrich (1985), we find information transfers exist between related industries. Hypothesis 2 is supported by the evidence.

The directional information transfers might be related to the nature of the announcement, namely good news or bad news as in Han et al. (1989). To explore this possibility, we partitioned our sample into two groups, good news and bad news. If the SCAR of forecasting firm is positive when management earnings forecasts are released, we consider it as good (bad) news. We reported *SAR* (standardized abnormal returns) and *SCAR* for both groups in panel A of Table 6 and regression results in panels B and C of the same table.

Table 6 Good news and bad news in information transfers to related industries

Panel A: Daily and cumulative standardized abnormal returns

Event period		Good news (n=2,942)			Bad news (n=2,496)		
		t-test		Sign-test	t-test		Sign-test
		mean	t-statistic	positive%	mean	t-statistic	negative%
SAR_j	Day -1	0.155	7.74***	0.51***	-0.092	-4.16***	0.57***
	Day 0	0.34	17.17***	0.59***	-0.066	-2.98***	0.55***
	Day 1	0.091	4.37***	0.50**	-0.154	-6.85***	0.58***
$SCAR_j$		0.586	16.36***	0.57***	-0.311	-7.64***	0.59***

Panel B: Regression analysis

Sample \ Model	$SCAR\ (NF) = \beta_0 + \beta_1\ SCAR\ (F) + \varepsilon$				
	β_0	$t\ (\beta_0)$	β_1	$t\ (\beta_1)$	R^2
Good news (n=2,942)	0.442	7.26***	0.073	2.81***	0.01
Bad news (n=2,496)	0.407	5.92***	0.509	11.4***	0.06

Panel C: Regression analysis

Sample \ Model	$SCAR\ (NF) = \beta_0 + \beta_1\ SCAR\ (F) + \beta_2\ GOOD^*\ SCAR\ (F) + \varepsilon$						
	β_0	$t\ (\beta_0)$	β_1	$t\ (\beta_1)$	β_2	$t\ (\beta_2)$	R^2
Full Sample(n=5,438)	0.426	9.34	0.519	14.66***	-0.44	-8.77***	0.07

SAR_j : standardized abnormal returns (%), $SCAR_j$: cumulative standardized abnormal returns (%); *(**/***) designates 10% (5%/1%) significance level, two-tailed tests. GOOD: good news released by the forecast firm.

Panel A of Table 6 shows that *SCAR* is significantly positive in good news group and significantly negative in bad news group at 1% level. Regression results in panel B of Table 6 also indicate that the coefficient estimate of β_1 is significantly positive at 1% level for both groups. The evidence suggests that the information transfers exist between related industries regardless in the good news group or bad news group. To further test whether the strength of information transfers are different between good news group and bad news group, we set an dummy variable Good (if SCAR (F) >0, then Good = 1; otherwise; 0) and examine the coefficient of the interaction item between good news and *SCAR (F)*. In the panel C of Table 6, the result indicates that coefficient (β_2) of the interaction item is significantly negative at 1% level (coefficient = -0.439; t-value = -8.77). It means that the strength of information transfers is higher in the bad news group than good news group.

Before evaluating our last hypothesis, the levels of vertical relatedness is positive with the strength of information transfers, we reported the means test for *SAR* and *SCAR* for both groups of highly related and weakly related industries in panel A of Table 7 and corresponding regression results in panel B of the same table. Industries with VRI greater than the median of VRI are assigned to the highly related group and others are assigned to weakly related group.

Table 7 Differential vertical informational transfers

Panel A: Daily and cumulative standardized abnormal returns

Event period		Highly related (N=2,489)			Weakly related (N=2,949)		
		mean	Std.dev.	t-statistic	Mean	Std.dev.	t-statistic
SAR_j	Day -1	0.035	1.09	1.62	0.047	1.11	2.31**
	Day 0	0.141	1.09	6.45***	0.16	1.11	8.01***
	Day 1	-0.013	1.15	-0.58	-0.027	1.12	-1.35
$SCAR_j$		0.163	1.98	4.1***	0.183	2.08	4.81***

Panel B: Regression analysis

Model / Sample	$SCAR\ (NF) = \beta_0 + \beta_1\ SCAR\ (F) + \varepsilon$				
	β_0	$t\ (\beta_0)$	β_1	$t\ (\beta_1)$	R^2
Highly related	0.000	0.00	0.228	11.91***	0.06
Weakly related	0.141	3.76***	0.274	13.23***	0.06

SAR_j : standardized abnormal returns (%), $SCAR_j$: cumulative standardized abnormal returns (%).
*(**/***) designates 10% (5%/1%) significance level, two-tailed tests.

In panel A of Table 7, the SCAR is significantly different 0 at 1% significant level in both highly related group and weakly related group. In panel B of Table 7, both the coefficient estimates of β_1 in the two groups are significant at 1% level. To further examine whether the level of vertical relatedness and the nature of information (good news v.s. bad news) will impact the degree of information transfers, we divided the sample into good news and bad news groups in each group (highly related and weakly related industries group). The result is shown in panel A of Table 8. All of the SCAR in these four dimensions are significantly different from 0 at 1% level.

In order to test our final hypothesis, we create new variable, the interaction item between *VRI* and *SCAR (F)* as shown in model (6), to examine whether the coefficient of the interaction item (β_2) is significantly positive or not. The result is shown in panel B of Table 8. The result indicates that the coefficient estimate of β_1 is significantly positive at 1% level in full sample. That is, the strength of information transfers is positive with the degree of relatedness between industries. We also find the positive relation is stronger in bad news group after we separate the sample into good news and bad news. Hypothesis 3 is supported by the evidence of panel C of Table 8.

Table 8 Differential vertical informational transfers

Panel A: Forecasting firm is highly related								
Event period		Good news (n=1,472)			Bad news (n=1,017)			
		t-test		Sign-test	t-test		Sign-test	
		Mean	t-statistic	Positive%	Mean	t-statistic	Negative%	
SAR_j	Day -1	0.133	4.77***	0.50***	-0.106	-3.08***	0.57***	
	Day 0	0.332	12.11***	0.59***	-0.136	-4.00***	0.58***	
	Day 1	0.093	3.11***	0.50*	-0.168	-4.72***	0.59***	
$SCAR_j$		0.559	11.11***	0.57***	-0.410	-6.81***	0.59***	
Panel B: Forecasting firm is weakly related								
Event period		Good news (n=1,470)			Bad news (n=1,479)			
		t-test		Sign-test	t-test		Sign-test	
		Mean	t-statistic	Positive%	Mean	t-statistic	Negative%	
SAR_j	Day -1	0.176	6.16***	0.52***	-0.081	-2.84***	0.58***	
	Day 0	0.348	12.17***	0.58***	-0.017	-0.60	0.53***	
	Day 1	0.089	3.07***	0.51*	-0.145	-4.98***	0.58***	
$SCAR_j$		0.613	12.02***	0.57***	-0.243	-4.43***	0.59***	
Panel C: Regression analysis								
Model / Sample	$SCAR\ (NF) = \beta_0 + \beta_1\ SCAR\ (F) + \beta_2\ VIC^*\ SCAR\ (F) + \varepsilon_1$							
	β_0	$t\ (\beta_0)$	β_1	$t\ (\beta_1)$	β_2	$t\ (\beta_2)$	R^2	
Full sample	0.076	2.77**	0,208	12.3***	1.054	3.96***	0.06	
Good news	0.44	7.23***	0.054	1.88*	0.623	1.85*	0.01	
Bad news	0.39	5.66***	0.448	9.13***	1.328	2.94***	0.06	

SAR_j: standardized abnormal returns (%), $SCAR_j$: cumulative standardized abnormal returns (%). VIC: vertical relatedness index; *(**/***) designates 10% (5%/1%) significance level, one-tailed tests.

Pyo and Lustgarten (1990) observed that the direction and magnitude of information transfers is affected by the covariance of earnings of forecasting and non-forecasting firms. To examine this potential confounding effect, we refer Pyo and Lustgarten (1990) to replace *SCAR (F)* with the interaction items of *SCAR (F)* and the ratio of covariance of earnings of forecasting and non-forecasting firms to the variance of earnings of the forecasting firm in the regression model and repeated all of the regression analyses above. Untabulated results show that the coefficients of the interaction items in all models are not significant whether the sample are separated based on the characters of the information (good news v.s bad news) or based on the level of vertical relatedness. Contrary to Pyo and Lustgarten (1990), we can not find the evidence that information transfers across related industries can attribute to the firm-specific factors such as the covariance of earnings of forecasting and non-forecasting firms. We posit that information transfers across related industries could be resulted from industries factors in the information of management earnings forecast.

To evaluate the robustness of our results, we specified two alternative event periods: (-1, 0) and (0, +1). We re-estimated *SAR* and *SCAR* for these two alternative event periods using the two-index pricing model as well as the market model. We found that the results are qualitatively similar to those discussed earlier and are not reported. We also re-examine the results of Table 5 if the sample only include VIC >0.01, or 0.02, or 0.03 or 0.04...until > 0.1. The results are similar to those discussed earlier. Finally, to insure that our inference is reasonable, we conduct the following two additional checks: heteroscedasticity and influential observations. We did not find evidence for heteroscedasticity and the results remained unchanged after removing outliers from the estimation.

5. Concluding Remarks

In this paper, we empirically evaluate the association between manager's earnings forecasts and inter-industry information transfers. Using a market model, we find information transfers across related industries. In addition, we find that characteristics of the information transfers such as the level of relatedness between industries and type of the news, good vs. bad, affect the magnitude of information transfers. In particular, we find the strength of information transfers are higher when management earnings forecasts are bad news. We also find that a positive relationship between the strength of information transfers and the relatedness between industries. Besides, using a two-index pricing model, we find information transfers after controlling for industry effects, too. Collectively speaking, our findings suggest that investors can use forecasting firms' management earnings forecast to revise their assessments in the prospect of their upstream or downstream industries and lead to the changes of stock prices in those industries. The strength of this kind of information transfers is associated with the industry characteristics that describe the level of interdependence between industries.

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