INSEAD

The Business School for the World®

Faculty & Research Working Paper

Analyst Following along the Supply Chain

Yuyan GUAN
Franco WONG
Yue ZHANG
2014/21/ACC

Analyst Following Along the Supply Chain

Yuyan Guan*

Franco Wong**

Yue Zhang***

January 6, 2014

Forthcoming in *Review of Accounting Studies*

We thank Joy Begley, Ling Cen, Sandra Chamberlain, Woo-Jin Chang, Sung Gon Chung, Gilles Hilary, Sharon Hudson, Artur Hugon, Peter Kennedy, Stan Markov, Michal Matejka, Steve Monahan, Suresh Radhakrishnan, Sundaresh Ramnath, Gordon Richardson, Tjomme Rusticus, Ram Venkataraman, Peter Wysocki, two anonymous reviewers, and workshop participants at the 10th Anniversary London Business School Accounting Symposium, the 7th Tel Aviv International Conference in Accounting, the IX International Accounting Research Symposium at Universidad Autónoma de Madrid, Arizona State University, City University of Hong Kong, Hong Kong Polytechnic University, INSEAD, Singapore Management University, University of British Columbia, University of Miami, and University of Toronto for their helpful comments and suggestions. Guan and Zhang acknowledge research start-up grants from the City University of Hong Kong. Wong appreciates financial support from the CMA Professorship in Accounting, the Social Sciences and Humanities Research Council of Canada, and INSEAD.

* City University of Hong Kong, College of Business, Knowloon, Hong Kong SAR, China. Email: yyguan@city.edu.hk

** Associate Professor of Accounting and Control at INSEAD, Boulevard de Constance 77305 Fontainebleau, France. Email: franco.wong@insead.edu

*** City University of Hong Kong, College of Business, Knowloon, Hong Kong SAR, China. Email: yuezhang@cityu.edu.hk

Abstract

We document that the likelihood of an analyst following a supplier-customer firm pair increases with the strength of the economic ties along the supply chain, as measured by the percent of the supplier's sales to the customer. Analysts who follow a covered firm's customer provide more accurate earnings forecasts for the supplier firm than analysts who do not. The greater forecast accuracy attributed to following a supplier's customer is as large as the effect of following the supplier's industry peers. While both types of analysts respond to and incorporate the earnings news from the customer firm into their revision of the supplier's earnings forecasts, we find no evidence that analysts who follow the supplier-customer pair do so at a greater extent than their counterparts. However, these supplier-customer analysts exhibit a larger improvement in their forecast accuracy for the supplier subsequent to the customer's earnings announcements, when compared to other analysts. Overall, the evidence suggests that supplier-customer analysts benefit from the informational complementarities along the supply chain and improve their forecast accuracy as a result.

Keywords: Supply chain; Information transfers; Analyst following; Forecast revisions; Forecast accuracy

JEL Classification: D80; G14; M41

Electronic copy available at: http://ssrn.com/abstract=2410151

1. Introduction

Firms are economically linked to each other in many ways, among which the supplier-customer link is an important one. The relation between suppliers and customers is explicit and sometimes delineated in contractual arrangements (Katz 1989; Costello 2011). Firms along the supply chain interact with each other directly through their trading relations, and indirectly through the market prices of their inputs and outputs (Menzly and Ozbas 2010). They are also exposed to similar demand/supply or technological shocks. Because of the strong economic ties existing between suppliers and customers, any value-relevant information about customers is expected to be value relevant for suppliers as well. Indeed, Olsen and Dietrich (1985), Hertzel et al. (2008), and Pandit et al. (2011) document evidence consistent with customers' news being informative for suppliers' stock prices in various settings.

In this paper, we examine the implications of the informational complementarities along the supply chain for analysts' coverage decisions, forecast revisions, and forecast accuracy. First, we expect that the stronger the economic bond between the supplier and customer firms, the more likely sell-side equity analysts will follow a covered firm's customer in order to benefit from complementary information along the supply chain.[1] Second, we predict that the analysts who cover the customer firm will be more accurate in forecasting the supplier firm's earnings than those analysts who do not follow the customer. Third, we conjecture that analysts who follow a firm's customer respond to and incorporate the customer's earnings news into their revisions of the supplier's earnings to a greater extent compared with other analysts. Finally, we predict that these supplier-customer analysts will exhibit a larger improvement in their forecast accuracy for the supplier firm than analysts who do not cover the customer, subsequent to the customer's earnings events.

[1] For ease of exposition, we assume that each supplier firm only has one major customer. In our data, some firms report more than one major customer and some analysts follow more than one of the firm's major customers.

Using a sample of firms with supplier-customer relations from 1982 to 2010, we document four key results. First, we find that the likelihood of an analyst covering a firm's customer is positively related to the percent of a firm's sales to that customer. Hence, the strength of the economic tie between the trading partners is an important consideration for analysts to decide whether to follow a covered firm's customer or not. Second, analysts who cover a firm's customer provide more accurate earnings forecasts for the firm than those analysts who do not. In fact, the effect from following a firm's customer on the analysts' forecast performance is at least as large as that from covering the firm's industry peers. This result is consistent with analysts benefiting from the complementary information between the customer and supplier firms.

Third, we examine whether the probability of the analyst issuing a forecast revision for the supplier within 14 days of the customer's earning announcements increases with the absolute magnitude of the earnings news and whether the magnitude of the forecast revision is positively associated with the magnitude of the customer's earnings news. While we document that both types of analysts respond to customer earnings news, we find no evidence that analysts who follow the supplier-customer pair react to the news to a larger extent than analysts who do not follow the customer firms. However, we show that analysts who cover the supplier-customer pair exhibit a larger improvement in their forecast accuracy for the supplier firm around the customer's earnings announcements than analysts who follow the supplier only. This is consistent with these analysts understanding the implications of the customer's earnings news for the supplier's earnings better than their counterparts and, therefore, using this knowledge more efficiently to make their forecast revisions for the supplier's earnings. This finding partly explains why analysts who cover both the supplier and customer are more accurate than those analysts follow the supplier firm only.

This study is related to several strands of literature in accounting and finance. First, we add to the literature on analyst portfolio choice. Prior research (e.g., Gilson et al. 2001; Chan and Hameed 2006) documents that analysts take advantage of the commonalities in the industry by covering multiple firms in the same industry. Kini et al. (2009) also find that analysts focus their coverage more on a sector as sector-based commonalities increase. On the other hand, other studies (e.g., Clement and Tse 2005; Boni and Womack 2006; Sonney 2009) show that analysts frequently cover firms from multiple industries/sectors, which can be beneficial if it exposes analysts to alternative sources of complementary information (Kini et al. 2009).[2] We use the supplier-customer relation to identify the potential existence of informational complementarities between firms from different industries. Hence, we add to this line of research by documenting that some analysts cover firms from different industries to benefit from informational complementarities between firms along the supply chain.[3]

Second, we contribute to the literature on the relation between analysts' portfolio specialization/diversification and their forecast accuracy. Prior studies point out that analysts face a difficult tradeoff when covering firms from different industries: potential gain from the information transfer among industries versus loss from spreading their resources too thin. Clement (1999) and Kini et al. (2009), among others, show that industry/sector-level diversification adversely affects analysts' forecast accuracy for U.S. firms. However, Kini et al. (2009) argue that diversification can potentially improve forecast accuracy if analysts take advantage of alternative sources of complementary information. Using the supplier-customer relation to identify informational complementarities between firms from different industries,

[2]Kini et al. (2009) examine the conditions under which analysts cover firms within a country or sector. Sonney (2009) examines the benefits of industry specialization versus country specialization.

[3]Koh et al. (2011) find that lenders take into consideration the characteristics of the borrower's customer when setting loan terms. Hence, their evidence complements our findings that sophisticated market participants use information along the supply chain.

we provide evidence supporting the argument of Kini et al. (2009).[4] Specifically, we show that analysts covering firms from different industries along the supply chain actually exhibit greater forecast accuracy than their counterparts who do not cover both firms.The difference in forecast accuracy is as large as that results from following a firm's peers in the same industry.

Third, previous studies have documented results consistent with the existence of vertical information transfer along the supply chain. In particular, Olsen and Dietrich (1985) find that the monthly sales announcements of firms in the retail industry affect the stock prices of their suppliers. Hertzel et al. (2008) document negative stock returns for the suppliers of firms that file for bankruptcy. Pandit et al. (2011) show that a firm's stock prices also react to the earnings surprises of the firm's customer, and examine the cross-sectional variation of the market reactions, holding constant the analyst forecast revisions. In this study, we investigate analysts' use of the informational complementarities between firms along the supply chain. While the aforementioned studies examine suppliers' stock price reactions to news about a firm's customer, we focus on the responses of analysts and find that analysts, to a certain extent, react to customer's earnings news and incorporate it into the forecast revisions for the supplier firm. Hence, we provide evidence for a potential mechanism by which customer firm's earnings news is impounded into their supplier's stock price.[5]Although we do not find evidence supporting our conjecture that analysts following customer-supplier pair respond more strongly to customer news relative to the others, we show that the former attain greater improvement in forecast accuracy in response to customer's earnings news.

---

[4]In our sample, about 63% of the customer firms are not from the same industry as the supplier firm, based upon the I/B/E/S industry classification. In the empirical analysis, we control for the potential intra-industry effect of those pairs that are from the same industry.

[5]We assume that the future cash flows and earnings of a firm are positively correlated with those of its customer. However, this assumption might not always hold. For example, the growth and expansion of the customer firms may increase their bargaining power in setting prices and other sales terms favorable to themselves. The fact that such a possibility exists biases against obtaining results consistent with our prediction.

The rest of this paper is organized as follows. Section 2 reviews the related literature and develops testable hypotheses. Section 3 describes the sample. Section 4 presents the research design and corresponding empirical results. Section 5 concludes.

2. Hypotheses

2.1 Analyst coverage along the supply chain and analyst forecast accuracy

Analysts construct their coverage portfolios based on an evaluation of the costs and benefits of covering a firm. The costs for the analysts' coverage include time and other resources spent on researching the covered firm. The payoffs come from the sales of their research reports and the trading commissions they generate for their brokerage houses (Hayes 1998; Gilson et al. 2001). Moreover, accurate analysts are less likely to experience turnover (Call et al. 2009; Mikhail et al. 1999) and more likely to move up to a more prestigious brokerage firm (Hong and Kubik 2003). As a result, equity analysts have various incentives to construct the portfolio of firms they follow to enhance the investment value of the research they produce and to improve the accuracy of the earnings forecasts they make.

Prior research shows that analysts tend to specialize in a few industries/sectors (e.g., Gilson et al. 2001; Piotroski and Roulstone 2004; Chan and Hameed 2006). Industry-level information is important in the analysis of a firm, and analysts can take advantage of the commonalities in an industry by covering multiple firms in the same industry to enjoy economies of scale in information acquisition and production (Clement 1999). Consistent with this information efficiency (or economy of scale) hypothesis, Kini et al. (2009) find that analysts focus their coverage more on a sector as sector-based commonalities increase.

However, prior studies also find that analysts frequently cover firms from multiple industries (e.g., Clement and Tse 2005; Boni and Womack 2006; Sonney 2009) and that for U.S. firms there is a negative relation between analyst forecast accuracy and the number of industries/sectors an analyst follows (Clement 1999; Kini et al. 2009). While a diversified portfolio may reduce scale economies, Kini et al. (2009) argue that it can potentially improve forecast accuracy. This is because analysts can benefit from the information complementarities among firms from different sectors or countries that are exposed to similar risk factors. In other words, the impact of analyst portfolio choice on forecast accuracy is a result of the tradeoff between the cost and benefit of covering firms from different industries along the supply chain.

On the one hand, following a firm's customer will distract an analyst if her coverage portfolio becomes more complex, especially when the customer firm is from a different sector or industry than the supplier. On the other hand, it is important and beneficial for analysts to follow firms along a supply chain for at least two reasons. First, the costs and revenues of the suppliers and customers are closely related. Researching the customers of a supplier provides the analyst a better understanding of the supplier's profit drivers and helps the analyst to make better predictions of the firm's earnings. Second, firms along the supply chain are influenced by some common factors, such as price, supply/demand, or technological shocks. Hence, following a firm's customer can benefit the analyst by exploiting the vertical information transfer along the supply chain. The information that the analyst obtains about the customer firm will provide useful indicators for the corresponding supplier.

We argue that the marginal benefit of including a customer in the coverage portfolio increases with the economic importance of the customer to the supplier. This is because the stronger the economic link along the supply chain, the greater will be the information complementarity between supplier and customer firms. Indeed, Pandit et al. (2011) document that the information externality increases with the strength of the economic bond between a supplier and its customer. When the marginal benefits of supplier-customer information spill overs exceed the marginal costs to the analysts from increasing the size and complexity of their coverage portfolios, they will choose to add the customer to their research universes. This discussion leads to our first testable hypothesis (stated in alternative form):

H1: Ceteris paribus, the likelihood of an analyst following a covered firm's customer is positively associated with the strength of the economic link between the two firms.

Various economic and non-economic factors determine analysts' forecast accuracy, such as a firms' information environment (Brown et al.1987; Kross et al. 1990; Lang and Lundholm 1996), an analyst's ability and skills (Clement 1999; Mikhail et al. 1997; Clement et al. 2007; Bae et al. 2008), government regulation (Heflin et al. 2003), and an analyst's portfolio choices (Clement 1999; Kini et al. 2009; Sonney 2009). While the relation between sector diversification and forecast accuracy is unclear (Kini et al. 2009), we argue that it can be beneficial for analysts to diversify their portfolio along the supply chain. This is because the information complementarity effect will likely surpass the loss of scale economies, given the strong economic link between customer and supplier firms. We thus conjecture that an analyst's decision to cover a firm's customer will be associated with higher forecast accuracy. The hypothesis (stated in alternative form) is stated as follows:

H2: Ceteris paribus, analysts who cover a firm's customer provide more accurate earnings forecasts for the firm than analysts who do not cover the customer.

2.2 Analyst response to customer's earnings news and improvement in forecast accuracy

Olsen and Dietrich (1985), Hertzel et al. (2008), and Pandit et al. (2011) examine inter-industry information transfer along the supply chain. Specifically, Olsen and Dietrich (1985) find that the monthly sales announcements of firms in the retail industry affect the stock prices of their suppliers and other firms in the supplier's industry. Hertzel et al. (2008) find negative stock returns for the suppliers of firms that filed for bankruptcy. Pandit et al.

(2011) show that the degree of information transfer along the supply chain is positively related to the economic bond between the supplier and customer, seasonal changes in the customer's revenue and cost of goods sold, and macro economic uncertainty. In sum, information spillovers along the supply chain exist: the earnings news of a customer firm is informative about its suppliers' stock prices.[6]

We examine analyst coverage of firms along the supply chain as a mechanism that help incorporate customer firm's earnings news into the supplier's stock prices. It is reasonable to believe that analysts take into consideration the information complementarities between the supplier and customer firms when making their forecast revisions. However, we are interested in whether analysts who cover a firm's customer are more responsive to the customer firm's earnings news than those analysts who do not cover the customer firm and whether analysts who cover the customer firm put more weight on the customer's earnings news when revising their forecasts for the supplier firm, compared to analysts who cover the supplier only. In summary, we test the following two hypotheses (stated in alternative form):

H3: Ceteris paribus, the relation between the absolute magnitude of a customer's earnings news and the likelihood that an analyst will revise her earnings forecast for the supplier firm is stronger for analysts who cover the customer firm than for those who do not.

H4: Ceteris paribus, the relation between the analyst's earnings forecast revision for the supplier firm and the earnings news of the customer firm is stronger for analysts who cover the customer firm than for those who do not.

Finally, we expect analysts who cover the customer-supplier pair to benefit more from incorporating complementary information from the customer firm when revising their forecasts for the supplier firm. We examine one potential benefit here: improvement in

[6] See Foster (1981), Han and Wild (1990), Ramnath (2002), and Thomas and Zhang (2008) on intra-industry information spillovers.

forecast accuracy. We hypothesize that analysts who follow a supplier's customer utilize the customer's earnings news more efficiently than those who do not. Therefore, the improvement in the accuracy of their earnings forecasts for the supplier firm subsequent to the customer's earnings news events is larger than that of their counterparts who do not follow the customer. The hypothesis (stated in alternative form) is as follows:

H5: Ceteris paribus, analysts who cover the supplier's customer firm experience a larger improvement in forecast accuracy than those who do not follow the customer, subsequent to the customer's earnings news releases.

3. Sample and data

Our initial sample consists of supplier-customer firm pairs over the period from January 1982 to December 2010. *SFAS No*. 14 and *SFAS No*. 131 (per SEC Regulation S-K Item 101) require firms to disclose the identities of customers representing more than 10% of their total sales.[7] We retrieve the names of the customers for each firm from the *COMPUSTAT* Industry Segment Customer file. As in Fee and Thomas (2004), we use the customer name to manually match the customer to a firm on the *COMPUSTAT* Industrial file. If a match is found, we retrieve the corresponding identifiers of the customer firms (GVKEY from the *COMPUSTAT* Industrial file and *I/B/E/S* ticker from *I/B/E/S*). Table 1, column (2) presents the number of supplier-customer pairs in our sample by year. The number increases gradually from 1,257 pairs in 1982 and peaks at 2,921 pairs in 1996. This results in 63,589 supplier-customer-year pairs over the 29-year sample period. Statistics not tabulated show that our sample consists of 38,749 distinct supplier-year relationships, representing a total of 21,036 unique supplier–customer relationships between 1982 and 2010.

To test hypothesis *H1* regarding the analyst's decision on whether or not to follow the customer of a firm in her coverage portfolio, we start with a sample of analysts who

[7] SFAS No.131 was issued by FASB in 1997 to govern segment disclosure. It becomes effective for fiscal years beginning after December 15, 1997, replacing SFAS No.14.

followed the supplier firm of each supplier-customer pair in each year. An analyst is said to be covering a firm in year *t* if she issues at least one annual earnings-per-share forecast for the firm in year *t*. We exclude supplier-customer pairs from our sample, if the analyst followed the customer firm before adding the supplier firm to her portfolio. Column (3) in table 1 indicates that there are a total of 28,212 supplier-customer pairs with at least one analyst covering the supplier firm over the entire sample period. Since some suppliers have multiple customer firms and have more than one analyst following them, we have a total of 229,250 analyst-supplier-customer-year observations (column 4). This is the sample we use to test hypothesis *H1*, but the actual number of observations used is lower because of missing data for some of the control variables.

To test hypothesis *H2* regarding the impact of following a firm's customer(s) on the analyst's forecast accuracy for the supplier firm, we use all analyst-supplier-year observations with at least two *I/B/E/S* analysts covering the supplier firm. Table 1, column (5) shows that the number of analyst-supplier-year observations is 140,309 over the sample period. The numbers reported under column (5) are lower than those reported under column (4), because some suppliers have more than one major customer. The actual number of observations used in testing hypothesis H2 is reduced due to the requirement that at least two analysts cover the supplier firm and missing data for some of the control variables.

The examination of hypotheses *H3* and *H4* starts with the sample used to test hypothesis *H1*. From that sample, we include all observations with an earnings news event from the customer firm. Earnings news events include both quarterly and annual earnings announcements. To test hypothesis *H5*, we start with the same sample we used to examine hypotheses *H3* and *H4*. However, we require the analyst forecasts issued before the customer's earnings news event to be no more than 90, 60, or 30 days old to avoid the use of stale earnings forecasts when computing the improvement of analyst forecast accuracy.

We retrieve financial statement data from *COMPUSTAT*, stock information (stock prices, the number of shares outstanding, and trading volume) from the *CRSP* monthly database, and analyst earnings forecasts and actual earnings data from the *I/B/E/S* Detail History database. The constructions of all the regression variables are described in the subsequent sections and summarized in the appendix.

4. Empirical analyses

4.1 Analyst coverage along the supply chain and analyst forecast accuracy

4.1.1Analyst propensity to follow a firm's customer

We use the following Cox proportional hazard model to investigate the economic determinants of an analyst's decision on whether or not to follow a covered firm's customer (hypothesis *H1*):

$$\begin{aligned} h(t) = h_0(t)\ exp(&\beta_0 + \beta_1 C\_Sale_{jkt-1} + \beta_2 Ln\_C\_MV_{jkt-1} + \beta_3 C\_Volume_{jkt-1} + \beta_4 C\_Leverage_{jkt-1} \\ &+ \beta_5 CS\_in\_SameInd_{jkt} + \beta_6 C\_in\_CoreInd_{ijkt} + \beta_7 N\_OtherAnalyst\_Follow\_C_{ijkt} \\ &+ \beta_8 Ln\_Firm\_MV_{jt-1} + \beta_9 N\_OtherAnalyst\_Follow\_Firm_{ijt} \\ &+ \beta_{10} Gen\_Exp_{it} + \beta_{11} Firm\_Exp_{ijt} + \beta_{12} Num\_Firm_{it} + \beta_{13} Broker\_Size_{it} \\ &+ \beta_{14} Broker\_Follow\_C_{ijkt} + \beta_{15} FD_t + Year\ Dummies). \end{aligned} \quad (1)$$

We estimate equation (1) using a sample of *I/B/E/S* analysts who covered the supplier firms before adding the customer firm to their portfolios. For each analyst-supplier-customer observation, we start the sample from the year when customer firm *k* first became a major customer of supplier firm *j* and analyst *i* follows supplier *j* but not customer *k*. Equation (1) relates the time that passes before analyst *i* initiates coverage of customer *k* to the economic bond between the supplier and its customer and other factors discussed below.

As stated in hypothesis *H1*, we expect the propensity to initiate coverage of the customer firm increases with the importance of the customer to the supplier. We capture the importance of the economic link between supplier *j* and its customer *k* using C_Sales_{jkt-1}, which is the percent of firm *j*'s sales to its customer *k* in year *t-1*. Hypothesis *H1* predicts that the estimated coefficient on C_Sales_{jkt-1} will be positive.

We include a number of variables to control for the potential impact of several customer firm's characteristics on the analyst's likelihood of covering that firm. $Ln\_C\_MV_{jkt-1}$ is the natural logarithm of the equity market capitalization of *j*'s customer firm *k* at the end of year *t-1*. Firm size can influence both the demand for and supply of analyst services (Bhushan 1989). The demand for analyst services increases with the size of the firm and, hence, an analyst may be more inclined to follow large firms. Firm size also affects the cost of acquiring information. On the one hand, large firms are likely to have more complex business structures or operations, making it more costly for the analyst to cover them. On the other hand, large firms usually provide more public disclosure and thus lead to less costly information acquisition. Therefore, it is unclear how customer firm size would affect the likelihood for the analyst to cover it. C_Volume_{jkt-1} is the annual trading volume (in thousands of shares) of firm *j*'s customer *k* in year *t-1* (Barth et al. 2001). The analyst may be more likely to follow stocks with high trading volumes, because they help sell her research and generate trading commissions for her brokerage house. $C\_Leverage_{jkt-1}$ is the leverage of firm *j*'s customer *k* in year *t-1*. It is calculated as *k*'s book value of total liabilities divided by the sum of the book value of total liabilities plus the market value of owners' equity. High-leverage firms may have a greater demand to access the equity markets, thus generating greater need for analyst following. $CS\_in\_SameInd_{jkt}$ takes the value of one if the firm and its customer are in the same *I/B/E/S* industry in year *t*. If the supplier and customer firms are in the same industry, it is more cost effective for an analyst to cover both firms. The inclusion of this variable also controls for intra-industry effect and, hence, the estimated coefficient on C_Sales_{jkt-1} can be interpreted as the incremental inter-industry effect (information complementarities). $C\_in\_CoreInd_{ijkt}$ takes a value of one if firm *j*'s customer *k* belongs to analyst *i*'s core industry in year *t*. If customer *k* is in the core industry of the analyst, the marginal cost to the analyst of covering it will be relatively low. Therefore, we expect a positive coefficient on $C\_in\_CoreInd_{ijkt}$. We define an analyst's core industry as the one that the majority of the firms covered by the analyst come from; industry membership is defined in *I/B/E/S*. $N\_OtherAnalyst\_Follow\_C_{ijkt}$ is the number of analysts other than analyst *i* that follow firm *j*'s customer *k* in year *t*. If there are other analysts following customer firm *k*, it will be less costly for analyst *i* to follow it too, but there could also be less need for her to cover it, given that she can use the publicly available research on firm *k*. Hence, we do not have a prediction for this variable.

We next include the following variables to control for the characteristics of supplier firm *j*. $Ln\_Firm\_MV_{jt-1}$ is the market value of firm *j*, measured as the natural logarithm of the equity market capitalization of the firm at the end of year *t-1*. The impact of firm *j*'s size is unclear. On the one hand, the bigger firm *j* is, the greater the marginal benefit (because of demand for research reports and increased trading commission revenue) for the analyst to enhance her research on firm *j* by also covering its customer. On the other hand, large firms tend to have rich information environment, making it less important for the analyst to search for more information on their customers. Hence, we do not predict the sign of the coefficient on $Ln\_Firm\_MV_{jt-1}$ ex ante. $N\_OtherAnalyst\_Follow\_Firm_{ijt}$ refers to the number of analysts other than analyst *i* who follow supplier firm *j* in year *t*. The greater the number of analysts following supplier *j*, the higher the competition. As a result, it may be more likely that an analyst who is covering firm *j*'s customer will have a competitive advantage over other analysts following the same supplier firm. Hence we predict $N\_OtherAnalyst\_Follow\_Firm_{ijt}$ to have a positive sign.

We also control for analyst characteristics that have been shown to affect portfolio choices (e.g., Kini et al. 2009). Gen_Exp_{it} is analyst *i*'s general forecasting experience in year

t, measured by the number of years since she issued her first earnings forecast for any firm according to the *I/B/E/S* database beginning in year 1981. We expect that a more experienced analyst is more likely to cover the customer firm, since she might have been exposed to firms in related industries and have experience over her career exploring outside her core industry. $Firm\_Exp_{ijt}$ represents the analyst's specific experience in following supplier firm j, measured by the number of years for which she has issued any forecast for firm j as of year t. We expect $Firm\_Exp_{ijt}$ to have a positive effect on the likelihood that the customer firm will also be followed, because the longer the analyst has followed the supplier firm, the more likely that the analyst knows about the firm's customers. Num_Firm_{it} is the number of companies in the analyst's portfolio. The larger the analyst's portfolio, the less time she has to cover an additional company. $Broker\_Size_{it}$ is the number of analysts employed by the brokerage firm that analyst i works for in year t. On the one hand, the bigger the brokerage firm, the more resources the analyst has to conduct her research. It may be less costly for the analyst from big brokerage firm to add the customer firm to her coverage portfolio. On the other hand, analysts from large brokerage firms tend to specialize in a small set of industries. Hence, the effect of brokerage size is an empirical question. $Broker\_Follow\_C_{ijkt}$ is an indicator variable that takes a value of one if at least one other analyst working in the same brokerage house as analyst i follows customer firm k in year t, and zero otherwise. If another analyst in the same brokerage firm is already covering customer firm k, analyst i can easily get the relevant information on firm k from her peer. Meanwhile, it is not likely that a brokerage house will assign more than one analyst to cover the same firm, unless they work as a team (Brown and Hugon 2009). Hence, we expect the estimated coefficient to be negative.

Finally, we control for the potential effect of Regulation Fair Disclosure (Reg FD), which became effective on October 23, 2000, to address selective disclosures of material non-public information to security analysts and institutional investors (e.g., Heflin et al. 2003;

Bailey et al. 2003; Markov and Gintschel 2004; Agrawal et al. 2006). FD_t is an indicator variable that takes the value of one if year *t* is greater than year 2000; otherwise, it equals zero.

Table 2, panel A presents summary statistics on these regression variables. Over the period 1982–2010, we have a total of 132,676 useable analyst-supplier-customer-year observations: 1,015 analysts start following a covered firm's customer (*Follow_C*=1) and 131,661 analyst-year observations with analysts covering the supplier only (*Follow_C*=0).[8] Mean C_Sales_{jkt-1} is statistically larger in the *Follow_C*=1 subsample than in the *Follow_C*=0 subsample (18% versus 16%). The customer firms in these two subsamples are similar in size, $Ln\_C\_MV_{jkt-1}$ and leverage, $C\_Leverage_{jkt-1}$. However, compared to the *Follow_C*=0 subsample, the customer firms in the *Follow_C*=1 subsample are more likely to have a higher trading volume, C_Volume_{jkt-1}, to be in the same industry as the supplier, $C\_in\_SameInd_{jkt}$ (56% versus 20%), to be in the core industry of the analyst, $C\_in\_CoreInd_{ijkt}$ (49% versus 23%), and to have more analysts following them, $N\_OtherAnalyst\_Follow\_C_{ijkt}$ (30.49 versus 24.53). Moreover, the supplier firms in the *Follow_C*=1 subsample are larger ($Ln\_Firm\_MV_{jt}$) and have more analysts following them ($N\_OtherAnalyst\_Follow\_Firm_{ijt}$) than their counterparts in the *Follow_C*=0 subsample. Finally, the analysts in the *Follow_C*=1 subsample have less general experience, but more firm-specific experience, and cover more companies than those in the *Follow_C*=0 subsample.

Table 2, panel B presents the estimation results of the hazard model (1). The sample contains 32,935 analyst-supplier-customer groups and 62,636 analyst-supplier-customer-year observations. Since the unit of analysis is the analyst-supplier-customer, we cluster the standard errors by analyst and firm. The estimated hazard coefficients and the associated z-statistics are reported under columns (3) and (4), respectively. Column (5) presents the hazard

[8] Once an analyst initiates coverage of a customer firm, the subsequent analyst-supplier-customer observations are excluded from the estimation of the hazard model. Hence, the *Follow_C=1* subsample only has 1,015 observations.

ratio (the exponential of the coefficient), which is one plus the marginal effect of changing the explanatory variable by one unit.

Consistent with our prediction, the estimated coefficient on *C_Sales*$_{jkt-1}$, our main variable of interest, is positive and significant at the 1% level. Column (5) shows that its hazard ratio is 2.339, indicating that as *C_Sale*$_{jkt-1}$ increases by 1 unit and all other control variables are held constant, the likelihood that an analyst will add the customer of a covered firm to her portfolio increases by 133.9% (=2.339 – 1).

As expected, the characteristics of the customer firm affect its propensity of being covered. In particular, trading volume and leverage (*C_Volume* and *C_Leverage*) increase the propensity of coverage. The estimated coefficient on *C_in_CoreInd* is statistically positive, consistent with the lower marginal cost of covering the customer firm in the analyst's core industry. The positive coefficient on *N_OtherAnalyst_Follow_C* suggests that the more other analysts follow the customer firm, the more likely it is that analyst *i* will also cover the customer firm. The characteristics of the supplier firm also affect whether the analyst covers the supplier's customer or not. In particular, we document a significantly positive coefficient on *Ln_Firm_MV*, consistent with the analyst being more likely to follow the customer of a large firm. As indicated by the negative coefficient on *N_otherAnalyst_Follow_Firm*, the analyst is less likely to cover the customer of a supplier firm with a large analyst coverage, which is inconsistent with this variable capturing the competitive reasons for the analyst to also follow the customer firm.

Regarding the effect of analyst characteristics on the decision to cover a firm's customer, the results show that the analyst with more general experience is less likely to cover the customer firm, as shown by the negative coefficient on *Gen_Exp*. On the other hand, the estimated coefficient on *Firm_Exp* is insignificantly negative.[9] We find a statistically negative coefficient on *Num_Firm*, which is consistent with the prediction that a busy analyst is less likely to add an additional coverage to his/her portfolio.

Finally, the estimated coefficient on *FD* is significantly negative. This result suggests that the propensity for an analyst to follow a covered firm's customer decreases in the post Reg-FD period. The hazard ratio equals 0.579, suggesting that the likelihood that an analyst will add the customer of a covered firm to her portfolio decreases by 42.1% (=1 - 0.579) after Reg FD, holding other control variables constant. This result is consistent with that documented by Irani and Karamanou (2003) over their sample period 1995-2001.

4.1.2 Coverage decision and analyst forecast accuracy for the supplier firm

We use the following regression to test hypothesis *H2* that analysts who cover a supplier firm's customer exhibit a higher forecast accuracy for the supplier firm than those analysts who do not:

$$\begin{aligned} Accu\_Score_{ijt} = {} & \beta_0 + \beta_1 Dum\_Follow\_C_{ijt} + \beta_2 Dum\_Broker\_Follow\_C_{ijt} \\ & + \beta_3 Dum\_C\_in\_CoreInd_{ijt} + \beta_4 Dum\_CS\_in\_SameInd_{ijt} \\ & + \beta_5 Follow\_Ind_{ijt} + \beta_6 Num\_Ind_{it} + \beta_7 Days\_Elap_{ijt} + \beta_8 For\_Hor_{ijt} \\ & + \beta_9 For\_Freq_{ijt} + \beta_{10} Gen\_Exp_{it} + \beta_{11} Firm\_Exp_{ijt} + \beta_{12} Broker\_Size_{it} \\ & + \beta_{13} Num\_Firm_{it} + \beta_{14} Ln\_Firm\_MV_{jt-1} + \varepsilon_{ijt}\,. \end{aligned} \tag{2}$$

We estimate equation (2) using a sample of *I/B/E/S* analysts who cover the supplier firms. Hence, the unit of analysis is the analyst-supplier-year. The dependent variable, $Accu\_Score_{ijt}$, is analyst *i*'s accuracy score for firm *j* in year *t*, which measures analyst relative forecast accuracy. Following Hong and Kubik (2003), among others, we calculate the analyst accuracy score as follows:

$$Accu\_Score_{ijt} = 100 - 100 \times \left\{ \frac{Rank_{ijt} - 1}{NumberFollowing_{jt} - 1} \right\},$$

[9]The findings on *Gen_Exp* and *Firm_Exp* are opposite to our prediction. To rule out the possibility that the correlation between *Gen_Exp* and *Firm_Exp* induce these findings, we include only one of these two variables into the model at a time. Untabulated results show that the estimated coefficients are both statistically negative.

where $Rank_{ijt}$ is analyst *i*'s forecast error rank for company *j* in year *t*, and $NumberFollowing_{jt}$ is the number of analysts following company *j* in year *t*. Forecast error for $Rank_{ijt}$ is computed as the absolute value of firm *j*'s actual earnings per share in year *t*, minus the most recent earnings- per-share forecast issued by analyst *i* at least one month prior to the end of fiscal year *t*. By construction, $Accu\_Score_{ijt}$ controls for cross-sectional differences in forecasting difficulty across companies.

Our main variable of interest is $Dum\_Follow\_C_{ijt}$, an indicator variable equal to one if analyst *i* covers at least one customer of firm *j* in year *t*, and zero otherwise. We conjecture that following a firm's customer allows the analyst to obtain valuable information about the firm's future profitability and leads to greater forecast accuracy (hypothesis *H2*). We thus expect a positive coefficient on *Dum_Follow_C*.

We take into account several factors that could affect analyst forecast accuracy in our setting. First, the analyst may have advance access to useful information about the customer firm if one of her colleagues follows the customer firm. Therefore, we include $Dum\_Broker\_Follow\_C_{ijt}$ and expect its estimated coefficient to be positive. Second, if the customer firm is in the core industry of analyst *i*, the analyst has a competitive advantage to acquire and assess information on the customer firm. We capture this construct using $Dum\_C\_in\_CoreInd_{ijt}$ and predict a positive estimated coefficient on it. Third, if the supplier and customer firms are in the same industry, it is more cost effective for an analyst to cover both firms. We include *Dum_CS_in_SameInd* and expect a positive coefficient. The constructions of these variables are similar to those in section 4.1.1 and are summarized in the appendix.

We also control for a number of factors that have been shown to affect analyst forecast accuracy in the prior literature (e.g., Clement and Tse 2005; Kini et al. 2009). $Follow\_Ind_{ijt}$ is an indicator variable that takes the value of one if analyst *i* follows at least one other firm in supplier *j*'s industry in year *t*; zero otherwise. We expect a positive coefficient on *Follow_Ind*, because it is more efficient for the analyst to follow more than one firm in the same industry. Num_Ind_{it} is the number of I/B/E/S industries followed by analyst *i* in year *t*. We expect a negative coefficient on *Num_Ind*, because sector diversification has shown to reduce forecast accuracy.[10] $Days\_Elap_{ijt}$ is the length of time in days between the year *t* earnings forecast for firm *j* by analyst *i* and the previous forecast of firm *j*'s year *t* earnings issued by any analyst. This variable measures the tendency of earnings forecasts to cluster, and controls for the release date of relevant information. For_Hor_{ijt} is the number of days between the date on which analyst *i* issues the earnings forecast for year *t*'s earnings and the fiscal year end date. It is used to capture the age of analyst *i*'s outstanding forecast. For_Freq_{ijt} is the number of times analyst *i* issues forecasts for firm *j* during year *t*. It is used to control for the analyst's effort.

Since prior studies (e.g., Clement 1999) show that more experienced analysts provide more accurate forecasts, we include both the analyst's firm-specific experience ($Firm\_Exp_{ijt}$) and general forecasting experience (Gen_Exp_{it}) in the model. We also control for the size of the brokerage firm ($Broker\_size_{it}$) that the analyst works for. A large brokerage firm not only has more resources available to the analyst, but it is also able to hire and attract more capable analysts. Hence, this variable also controls for other innate differences in analyst ability, beyond $Firm\_Exp_{ijt}$ and Gen_Exp_{it}. To control for the effort an analyst (likely) expends on covering the stocks in her portfolio, we include the number of firms covered by the analyst (Num_Firm_{it}). Lastly, we control for the firm size ($Ln\_Firm\_MV_{jt-1}$). These variables are defined as in section 4.1.1 above.

Table 3, panel A presents our summary statistics. There are 117,919 analyst-supplier-year observations and 21,919 (18.6%) of them have *Dum_Follow_C* equal to one.

[10] Clement (1999) shows that industry specialization improves analysts' forecast accuracy. Although Kini et al. (2009) argue that the relation between sector diversification and forecast accuracy is context-specific, they document a negative relation for a sample of U.S. firms.

Both the mean and median of *Accu_Score* for the *Dum_Follow_C*=1 subsample are greater than those for the *Dum_Follow_C*=0 subsample. These statistics provide preliminary evidence suggesting that earnings forecasts issued by analysts who follow both the supplier and customer are more accurate than those by analysts who follow the supplier only. In the *Dum_Follow_C*=1 subsample, 36% of the analysts have a peer at their brokerage firm who follows at least one of firm *j*'s customer firms (i.e., $Dum\_Broker\_Follow\_C_{ijt}$ =1), compared to 47% in the *Dum_Follow_C=0* subsample. The average $Dum\_C\_in\_CoreInd_{ijt}$ value is larger in the *Dum_Follow_C*=1 subsample than in the *Dum_Follow_C*=0 subsample (69% versus 27%). The mean and median values of *Days_Elap*, *For_Hor*, *For_Freq*, and *Num_Firm* for the overall sample are similar to those reported in prior studies (Clement and Tse 2005; Kini et al. 2009). The mean of *For_Freq* for subsample *Dum_Follow_C*=1 is statistically smaller than that for subsample *Dum_Follow_C*=0, suggesting that those analysts who follow both the supplier and customer firms update their earnings forecasts for the supplier firms less frequently.

We estimate equation (2) using both Heckman's (1979) two-stage procedure and the two-stage least squares (2SLS) method to take into account endogeneity, because the individual analyst or her brokerage house decides whether or not to initiate coverage of a firm's customer. In the first stage of the Heckman procedure, we estimate a probit model similar to the one specified in equation (1), except that we use analyst-supplier-year observations in this analysis.[11] In the second stage, we include into equation (2) the Inverse Mills Ratio calculated from the first stage probit regression.

Table 3, panel B presents the estimation result of the second stage of the Heckman procedure in column (3). The estimated coefficient on *Dum_Follow_C* is positive and

[11] This is to account for the fact that the forecast accuracy regression is conducted at the analyst-supplier level. If a supplier has more than one customer, we use the largest customer to construct the corresponding explanatory variables. The result (not tabulated) for this regression is qualitatively similar to that reported in panel B of table 2.

statistically significant at the 1% level, consistent with our prediction that an analyst who follows a supplier firm's customer provides more accurate earnings forecasts for the supplier firm. The positive coefficient on *Dum_Broker_Follow_C* also confirms our conjecture that the analyst may also obtain valuable information on the customer from colleagues working in the same brokerage house, improving her forecast accuracy for the supplier firm. However, the estimated effect of *Dum_Broker_Follow_C* is small compared to that of *Dum_Follow_C*. Contrary to our expectation, the estimated coefficient on *Dum_C_in_SameInd* is statistically negative at the 10% significance level. On the other hand, we document a positive and significant coefficient on *Follow_Ind* and a significantly negative coefficient on *Num_Ind*, which are consistent with industry specialization improving forecast accuracy (Clement 1999).

Other control variables exhibit significant explanatory power for forecast accuracy. In particular, the estimated coefficient on *Days_Elap* is positive and significant, which is inconsistent with the result of Clement and Tse (2005) that forecasts clustered together tend to be more accurate. Similar to O'Brien (1988), we observe a negative coefficient on *For_Hor*, which indicates that earnings forecasts issued closer to the fiscal year end are more accurate as more information becomes available. As a proxy for the analyst's effort, *For_Freq* receives a positive coefficient, consistent with the previous finding that analysts who expend greater effort in following a firm issue more accurate forecasts (Clement 1999; Jacob et al. 1999). Prior literature provides mixed evidence on the impact of analyst general- and firm-specific experience on forecast accuracy (Clement 1999; Brown 2001; Clement and Tse 2005; Kini et al. 2009). Surprisingly, we document a negative coefficient on *Gen_Exp*, suggesting that the number of years an analyst has spent in the profession seems to reduce her forecast accuracy.[12] Consistent with prior studies, the estimated coefficient on *Broker_Size* is positive and that on *Num_Firm* is negative, even though they are statistically insignificant. Finally, the estimated coefficient on *FD* is statistically negative, suggesting that there is a decrease in analyst forecast accuracy in the post-Reg FD period. This is in contrast to Heflin et al. (2003), who find that Reg FD has an insignificant effect on the accuracy of analysts' earnings forecasts.

Next, we use 2SLS to estimate equation (2). In the first stage, we estimate the predicted probability of *Dum_Follow_C* using a probit model, which includes all the explanatory variables in the first stage of the Heckman procedure discussed above, as well as all the explanatory variables, except the endogeneity variable (i.e., *Dum_Folow_C*), in equation (2). In the second stage, we estimate equation (2) using the instrumental variable regression method, with the predicted probability from the first stage as an instrument for *Dum_Follow_C*. This procedure of handling a dichotomous endogenous variable produces correct standard errors and is more efficient than the usual 2SLS method (Wooldridge 2002, 623-625). Column (4) in panel B of table 3 presents the estimation of the second-stage regression. The estimated coefficient on our main variable of interest, *Dum_Follow_C*, is positive and significant. The estimation results on the other control variables are qualitatively similar to those in the Heckman regression reported in column (3), except that *Dum_C_in_CoreInd*, *Num_Firm*, and *Ln_Firm_MV* become significantly different from zero.

Finally, it has been shown in prior studies that industry specialization enhances an analyst's forecast accuracy, because firms within an industry are subject to many common economic forces. On the other hand, the evidence documented above is consistent with analysts benefiting from information along the supply chain. We compare the relative importance of these two economic links by using an *F*-test to test the equality of the

[12]To rule out the possibility that the correlation between *Gen_Exp* and *Firm_Exp* induce these findings, we include only one of these two variables in the regression at a time. However, the estimated coefficients are still statistically negative.

estimated coefficients on *Follow_Ind* and *Dum_Follow_C*. The results, reported in the last row of panel B in table 3, show that the two estimated coefficients are not significantly different from each other under the Heckman estimation method, but they are significantly different under the 2SLS method (with the coefficient on *Dum_Follow_C* being greater). In other words, information transfer along the supply chain has at least as much positive effect on analysts' forecast accuracy as does intra-industry information transfer.

4.2 Analyst's response to information transfer along the supply chain

4.2.1 Analysts' forecast revisions in response to the earnings news of a firm's customer

We use the following logistic regression models to examine whether the propensity of analysts to revise their earnings forecasts for the supplier firm in response to the earnings news of the customer firm is higher for analysts who cover both the supplier and customer firms than for analysts who only cover the supplier (i.e., hypothesis *H3*):

$$Prob(Dum\_REV_{ijkt}=1) = \beta_0 + \beta_1\, Abs(CES_{kt}) + \beta_2\, Abs(ES_{jt}) + \beta_3\, Abs(RET_{jt}) + \beta_4\, Follow\_C_{ijkt} + \beta_5 Abs(CES_{kt}) \times Follow\_C_{ijkt} + \varepsilon_{ijkt}\,, \quad (3)$$

where Dum_Rev_{ijkt} is an indicator variable that takes a value of one if analyst i revises her forecast of supplier j's one-year ahead annual earnings within 14 days after customer k's earnings announcement in time t, and zero otherwise. *Abs(.)* is the absolute value operator. CES_{kt} is the earnings surprise of customer k at its earnings announcement at time t, computed using analysts' consensus forecast and scaled by k's beginning stock price. ES_{jt} is the earnings surprise of the supplier firm j if analyst i has not revised her forecast for firm j since j's most recent earnings announcement at time t; otherwise, it equals zero. ES_{jt} is computed using analysts' consensus forecast and scaled by firm j's beginning stock price. RET_{jt} is firm j's market-adjusted return, calculated as its raw return minus the value-weighted market index return, accumulated from analyst i's previous forecast date for supplier j to customer k's earnings news event date. We use RET_{jt} to capture any value-relevant news about supplier j that was released between the previous forecast of analyst i and customer k's earnings news event. We expect that the bigger the customer firm's earnings news (in either direction), the higher the probability that the analyst will issue an earnings forecast revision for the supplier. Hence, the estimated coefficient on $Abs(CES_{kt})$ is predicted to be positive. We also expect the estimated coefficients on $Abs(ES_{jt})$ and $Abs(RET_{jt})$ to be positive. More importantly, a positive coefficient on the interaction term, $Abs(CES_{kt})*Follow\_C_{ijkt}$ is consistent with hypothesis *H3*.

Similarly, we use the following regression equation to test hypothesis *H4*:

$$REV_{ijkt} = \chi_0 + \chi_1 CES_{kt} + \chi_2 ES_{jt} + \chi_3 RET_{jt} + \chi_3 Follow\_C_{ijkt} + \chi_4 CES_{kt} \times Follow\_C_{ijkt} + v_{ijt}, \quad (4)$$

where REV_{ijkt} is analyst *i*'s revision of supplier *j*'s earnings within 14 days after customer *k*'s earnings announcement at time *t*. It is calculated as the difference between analyst *i*'s revised and prior forecasts of supplier *j*'s one-year-ahead annual earnings, scaled by the stock price of firm *j* a day before the issuance of analyst *i*'s prior forecast. CES_{kt}, ES_{jt}, *and* RET_{jt} are defined as in equation (3) above. We expect a positive coefficient on CES_{kt} if analyst *i* uses the earnings news of the customer firm *k* to update her earnings forecast for the supplier firm *j*. We also expect the estimated coefficients on ES_{jt} and RET_{jt} to be positive. Finally, a positive estimated coefficient on $CES_{kt}*Follow\_C_{ijkt}$ is consistent with hypothesis *H4*.

Table 4, panel A presents summary statistics on the regression variables. There are a total of 531,929 observations with customers' earnings announcements (quarterly and annually) and available data for all regression variables. 23.08% of the analysts who follow the customers of the firms they cover (i.e., *Follow_C*=1) revise their forecasts for the supplier firms within 14 days after the customer firms release their earnings (i.e., Dum_Rev_{ijkt}=1), compared to 22.25% for those analysts who do not (i.e., the *Follow_C*=0 subsample). The absolute magnitude of the customer's earnings surprises, *Abs(CES)*, is significantly larger in the *Follow_C=1* subsample than in the *Follow_C=0* subsample. Further, the *Follow_C=1* subsample exhibits a larger downward forecast revision (*REV*) than the *Follow_C=0* subsample.

Panel B, column (2) summarizes the estimation of equation (3). The estimated coefficient on *Abs(CES)×Follow_C* is not statistically different from zero. This suggests that analysts following the supplier-customer firm pair are no more likely to react to the earnings news of the customer when making their forecast revision decisions for the supplier than analysts who only follow the supplier firm. As an alternative test of hypothesis *H3*, columns (3) and (4) show that $Abs(CES_{kt})$ exhibits a significant and positive association with Dum_Rev_{ijkt} in both the *Follow_C=1* and *Follow_C=0* subsamples. This result indicates that both types of analysts incorporate the earning news of the customer firm when deciding to update their earnings forecasts for the supplier, holding constant other news, $Abs(ES_{jt})$ and $Abs(RET_{jt})$, about supplier *j*. While the estimated coefficient on $Abs(CES_{kt})$ is larger in the *Follow_C=1* subsample, untabulated statistic indicates that it is not significantly larger than that in the *Follow_C=0* subsample (5.551 vs. 2.940). In sum, hypothesis *H3* is not supported by the data.

Panel C, column (2) reports the estimation of equation (4). The estimated coefficient on *CES×Follow_C* is positive, but not significantly so. Columns (3) and (4) show that the estimated coefficients on CES_{kt} are statistically positive in both subsamples, suggesting that analysts take into consideration the earnings news of the customer firm (CES_{kt}) when revising their forecasts for the supplier. While the estimated coefficient on CES_{kt} is larger in the *Follow_C=1* subsample than that in the *Follow_C=0* subsample (0.013 vs. 0.011), untablulated statistic indicates that they are not statistically different from each other. Hence, hypothesis *H4* is not supported.

4.2.2 Improvement in analysts' forecast accuracy

In the last subsection, we find no support that analysts who cover both the supplier and customer firms respond to the customer earnings news more than those who only cover the supplier. In this section, we investigate whether the two types of analysts use the customer earnings news efficiently. Specifically, we examine whether analysts who follow the supplier-customer pair exhibit a greater improvement in their forecast accuracy for the supplier firm around the customer's earnings announcements, compared to those analysts who only follow the supplier firm (hypothesis *H5*).

We test hypothesis *H5* using the following regression model:

$$\begin{aligned} ACCIMP_{ijkt} = {} & \beta_0 + \beta_1 Follow\_C_{ijkt} + \beta_2 PreAFA_{ijt} + \beta_3 FRCHRZ_{ijt} \\ & + \beta_4 For\_Freq_{ijt} + \beta_5 Firm\_Exp_{ijt} + \beta_6 Gen\_Exp_{it} + \beta_7 Broker\_Size_{it} \\ & + \beta_8 Num\_Firm_{it} + \beta_9 Num\_Ind_{it} + \beta_{10} N\_OtherAnalyst\_Follow\_Firm_{ijt} \\ & + \beta_{11} Ln\_Firm\_MV_{jt-1} + \text{Year Fixed Effects} + v_{ijt}\,, \end{aligned} \tag{5}$$

where $ACCIMP_{ijkt}$ is improvement in forecast accuracy, computed as the change in analyst *i*'s forecast error for supplier *j* scaled by *j*'s stock price one day before customer *k*'s earnings announcement.[13] We compare the error of the earnings forecast issued within 14 days after the customer's earnings announcement to the error of the previous earnings forecast made by the same analyst. For those analysts who do not revise their forecast for the supplier firm within the 14-day window, the improvement in forecast accuracy is zero by construction.

$Follow\_C_{ijkt}$ is our variable of interest. A positive coefficient on $Follow\_C_{ijkt}$ is consistent with the improvement in forecast accuracy being greater for analysts who follow both the supplier and customer firms than those who follow only the supplier. The pre-event day forecast error, $PreAFA_{ijt}$, is the absolute value of the difference between analyst *i*'s earnings-per-share (EPS) forecast and the actual EPS of supplier firm *j* just before the customer firm's earnings announcement, scaled by *j*'s stock price one day before the event. We expect a positive coefficient on $PreAFA_{ijt}$, because analysts who are less accurate before

[13] This research design is adopted from Hilary and Shen (2013), which examines the effect of analysts' experience with a firm's management forecasts on their ability to utilize the earnings news of the firm's industry peers.

the earnings announcement will have more room for improvement (Hilary and Shen 2013). $FRCHRZ_{ijt}$ is the forecast horizon, measured as the number of days between the date of customer *k*'s earnings announcement and the date of analyst *i*'s forecast revision for supplier firm *j*. If analyst *i* does not revise her forecast after customer *k*'s earnings announcement, we set $FRCHRZ_{ijt}$ equal to the number of days from the customer firm's earnings announcement to the supplier firm *j*'s earnings announcement date minus 14. The other variables come from section 4.1 above.

Table 5 summarizes the estimation of equation (5). To avoid stale earnings forecasts, we restrict the prior forecasts used to compute $ACCIMP_{ijkt}$ to those issued within 90, 60 and 30 days before the customer's earnings announcement. We document a statistically positive coefficient on *Follow_C* for the 90- and 60-day windows under columns (2) and (3), respectively. For the 30-day window, the estimated coefficient on *Follow_C* is insignificantly positive, suggesting that newest forecasts have less room for improvement. Overall, this evidence supports hypothesis *H5* that analysts who follow the customer firm improve their forecast accuracy for the supplier firm to a greater extent than analysts who cover the supplier firm only.

5. Conclusion

We document evidence consistent with analysts constructing their research portfolios along the supply chain to take advantage of the vertical information transfer between customers and suppliers. In particular, we find that analysts are more likely to initiate coverage of a firm's customer the larger the percent of the firm's sales to that customer. Analysts who follow a firm's customer provide more accurate earnings forecasts for the supplier firms than analysts who do not. This greater forecast accuracy is at least as large as that derived from following a firm's industry peers. While both types of analysts incorporate the earnings news from the customer firm into their revision of the supplier's earnings, we find no evidence that analysts who follow the supplier-customer pair do so at a greater extent than those analysts who follow the supplier firm only. However, analysts who cover the supplier-customer pair exhibit a larger improvement in their forecast accuracy after the customer's earnings announcement than their counterparts, consistent with the formers using the customer earnings news more efficiently than the latters.

References

Agrawal, A.,Chadha, S., Chen M.A., 2006. Who is afraid of Reg FD? The behavior and performance of sell-side analysts following the SEC's fair disclosures rules. Journal of Business 79, 2811-2834.

Bae, K.H., Stulz, R., Tan, H., 2008. Do local analysts know more? A cross-country study of the performance of local analysts and foreign analysts. Journal of Financial Economics 88, 581–606.

Bailey, W., Li, H., Mao, C.X., Zhong, R, 2003. Regulation fair disclosure and earnings information: Market, analyst, and corporate responses. Journal of Finance 58, 2487-2514.

Barth, M.E., Kasznik, R., McNichols, M.F.,*2001*.Analyst Coverage and Intangible Assets.Journal of Accounting Research39, 1–34.

Bhushan, R.,1989. Firm characteristics and analyst following. Journal of Accounting and Economics 11, 255-274.

Boni, L., Womack, K. L., 2006. Analysts, industries, and price momentum. Journal of Financial and Quantitative Analysis 41**,** 85–109.

Brown, LD., Hagerman, R.L., Griffin, P.A., Zmijewski, M.E., 1987. Security analyst superiority relative to univariate time-series models in forecasting quarterly earnings. Journal of Accounting and Economics 9, 61-87.

Brown, L.D., 2001. A temporal analysis of earnings surprises: Profits versus losses. Journal of Accounting Research 39, 221-241.

Brown, L.D., Hugon, A., 2009. Team earnings forecasting. Review of Accounting Studies 14(4), 587-607.

Call, A., Chen, S., Tong, Y., 2009. Are earnings forecasts more accurate when accompanied by cash flow forecasts? Review of Accounting Studies 14: 358-391.

Chan, K., Hameed, A., 2006. Stock price synchronicity and analyst coverage in emerging markets. Journal of Financial Economics 80, 115-147.

Clement, M.B., 1999. Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? Journal of Accounting and Economics 27, 285-303.

Clement, M.B., Tse, S.Y., 2005. Financial analyst characteristics and herding behavior in forecasting. Journal of Finance 60, 307-341.

Clement, M.B., Koonce, L., Lopes, T., 2007. The role of task-specific forecasting experience and innate ability in understanding analyst forecasting performance. Journal of Accounting and Economics 44, 378-398.

Costello, A.M., 2011. Mitigating incentive conflicts in inter-firm relationships: Evidence from long-term supply contracts. Working paper, MIT.

Fee, C.E., Thomas, S., 2004. Sources of gains in horizontal mergers: Evidence from customer, supplier, and rival firms. Journal of Financial Economics 74, 423-460.

Foster, G., 1981. Intra-industry information transfers associated with earnings releases. Journal of Accounting and Economics 3, 201-232.

Gilson, S.C., Healy, P.M., Noe, C.F., Palepu, K.G., 2001. Analyst specialization and conglomerate stock breakups. Journal of Accounting Research 39, 565-582.

Han, J. and J. Wild. 1990. Unexpected earnings and intra-industry information transfer: Further evidence. Journal of Accounting Research 28, 211-219.

Hayes, R.M., 1998. The impact of trading commission incentives on analysts' stock coverage decisions and earnings forecasts. Journal of Accounting Research 36, 299-320.

Heckman, J.J., 1979. Sample Selection Bias as a Specification Error. Econometrica 47, 153-161.

Heflin, F., Subramanyam, K. R., Zhang Y., 2003. Regulation FD and the financial information environment: Early evidence. The Accounting Review 78, 1-37.

Hertzel, M. G., Li, Z., Officer, M. S., Rodgers, K. J., 2008. Inter-firm linkages and the wealth effects of financial distress along the supply chain. Journal of Financial Economics 87, 374-387.

Hilary, G., Shen, R., 2013. The role of analysts in intra-industry information transfer. Forthcoming in The Accounting Review.

Hong, H., Kubik, J., 2003. Analyzing the analysts: Career concerns and biased earnings forecasts. The Journal of Finance 58, 313-351.

Irani, A., Karamanou, I., 2003. Regulation Fair Disclosure, analyst following, and analyst forecast dispersion. Accounting Horizons 17(1), 15-29.

Jacob, J., Lys, T.Z., Neale, M., 1999. Expertise in forecasting performance of security analysts. Journal of Accounting Economics 28, 51–82.

Katz, M. L. 1989. Vertical contractual relations. R. Schmalensee, R. D. Willig, eds. Handbook of Industrial Organization, vol. I. Elsevier Science Publishers B.V., New York.

Kini, O., Mian, S., Rebello, M., Venkateswaran, A., 2009. On the structure of analyst research portfolios and forecast accuracy. Journal of Accounting Research 47, 867-909.

Koh, W.C., Teoh, S.H., Tham, T.M., 2011. How major customer affect supplier loan yield and covenants. Working Paper, Nanyang Technological University and UC Irvine.

Kross, W., Ro, B., Schroeder, D., 1990. Earnings expectations: The analysts' information advantage. The Accounting Review 65, 461-476.

Lang, M.H., Lundholm, R.J., 1996. Corporate disclosure policy and analyst behavior. The Accounting Review 71, 467-492.

Markov, S., Gintschel A., 2004.The effectiveness of Regulation FD. Journal of Accounting and Economics, 37 (3), 293-314.

Menzly, L., Ozbas, O., 2010. Market segmentation and cross-predictability of returns. Journal of Finance 65, 1555-1580.

Mikhail, M., Willis, R., Walther, B., 1997. Do security analysts improve their performance with experience? Journal Accounting Research 35, 131-157.

Mikhail, M. B., Walther, B. R., Willis, R. H., 1999. Does forecast accuracy matter to security analysts? The Accounting Review 74 (2):185-200.

O'Brien, P. C., 1988. Analysts' forecasts as earnings expectations. Journal of Accounting and Economics 10, 53-83.

Olsen, C., Dietrich, J. R., 1985. Vertical information transfers: The association between retailers' sales announcements and suppliers' security returns. Journal of Accounting Research 23, 144-166.

Pandit S., Wasley S., Zach T., 2011. Information externalities in capital markets: The economic determinants of suppliers' stock price reaction to their major customers' information events. Contemporary Accounting Research 28(4), 1304-1343.

Piotroski, J.D., Roulstone, B.T., 2004. The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices. The Accounting Review 79, 1119-1151.

Ramnath, S., 2002. Investor and analyst reactions to earnings announcements of related firms. An empirical analysis. Journal of Accounting Research 40(5), 1351-1376.

Sonney, F., 2009. Financial analysts' performance: Sector versus country specialization. Review of Financial Studies22, 2087–2131.

Thomas J., Zhang F., 2008. Overreaction to intra-industry information transfers. Journal of Accounting Research 46(4), 909-940.

Wooldridge, J.M., 2002. Econometric Analysis of Cross Section and Panel Data. MIT Press.

Appendix: Variable definitions

1. Dependent variables

$Follow\_C_{ijkt}$	An indicator variable for an analyst following a firm's customers. It takes the value of 1, if analyst *i* issues at least one annual forecast for firm *j*'s customer *k* in year *t*. Otherwise, it equals zero.
$Accu\_Score_{ijt}$	$Accu\_Score_{ijt}$ is equal to 100-100* ($Rank_{ijt}$ – 1) /($NumberFollowing_{jt}$ – 1), where $Rank_{ijt}$ is analyst *i*'s forecast error rank for firm *j* in year *t* and $NumberFollowing_{jt}$ is the number of analysts following firm *j* in year *t*. Forecast error is computed as the absolute value of firm *j*'s actual earnings in year *t* minus the most recent earnings forecast issued by analyst *i* at least one month prior to the end of fiscal year *t*.
Dum_REV_{ijkt}	An indicator that takes a value of one if analyst *i* revises her forecast of supplier *j*'s one-year-ahead annual earnings within 14 days after firm *j*'s customer *k* releases earnings in time *t*, and zero otherwise.
REV_{ijkt}	Analyst *i*'s revision of supplier *j*'s earnings within 14 days after customer *k*'s earnings announcement in time *t*. It is the difference between analyst *i*'s revised and prior forecasts on supplier *j*'s one-year-ahead annual earnings, scaled by the stock price of firm *j* the day before the issuance of analyst *i*'s prior forecast.
$ACCIMP_{ijkt}$	The change in analyst *i*'s forecast error for supplier *j* scaled by firm *j*'s stock price one day before customer *k*'s earnings news event.

2. Explanatory variables

$Broker\_Follow\_C_{ijkt}$	An indicator variable that takes the value of 1 if other analysts in analyst *i*'s brokerage house follow firm *j*'s customer *k* in year *t*. Otherwise, it equals zero.
$Broker\_Size_{it}$	The number of analysts employed in analyst *i*'s brokerage firm in year *t*.
CES_{kt}	Earnings surprise of customer firm *k* at its most recent earnings announcement in time *t*, computed using consensus forecast and scaled by the beginning stock price.
CMF_{kt}	Customer firm *k*'s management forecast news, computed using consensus forecast and scaled by the beginning stock price.
C_Sales_{jkt}	The percentage of firm *j*'s sales to its customer *k*. It equals firm *j*'s sales to its customer *k* divided by the firm's total sales in year *t*.
C_Volume_{jkt-1}	The annual trading volume of firm *j*'s customer *k* in year *t-1*.
$C\_Leverage_{jkt-1}$	The leverage ratio of firm *j*'s customer *k* in year *t-1, denoting* the book value of total liabilities divided by the sum of the book value of total liabilities and the market value of owners' equity.
$CS\_in\_SameInd_{jkt}$	An indicator variable that takes the value of 1 if the supplier *j* and its major customer firm *k* are in the same I/B/E/S industry; otherwise, it equals zero.
$C\_in\_CoreInd_{ijkt}$	An indicator variable takes the value of 1 if firm *j*'s customer *k* is in analyst *i*'s core industry in year *t*. Otherwise, it equals zero.
$Days\_Elap_{ijt}$	The number of calendar days between analyst *i*'s forecast date for the earnings of firm *j* in year *t* and the previous closest forecast date of any analyst for firm *j* in year *t*. This variable measures the tendency of forecasts to cluster.
$Dum\_Follow\_C_{ijt}$	An indicator for an analyst following a firm's customers. It takes the value of 1, if analyst *i* follows at least one of firm *j*'s customers in year *t*; otherwise, it equals zero.
$Dum\_Broker\_Follow\_C_{ijt}$	An indicator variable that takes the value of 1 if other analysts in analyst i's brokerage house follow at least one of firm j's customers in year t. Otherwise, it equals zero.
$Dum\_C\_in\_CoreInd_{ijt}$	An indicator variable takes the value of 1 if at least one of firm j's customers is in analyst i's core industry in year t. Otherwise, it equals zero.

(continued…)

Appendix (…continued)

$Dum\_CS\_in\_SameInd_{jt}$	An indicator variable that takes the value of 1 if the supplier j and at least one of its major customers are in the same I/B/E/S industry; otherwise, it equals zero.
ES_{jt}	Earnings surprise of the supplier firm *j* if analyst *i* has not revised her forecast for firm *j* since *j*'s most recent earnings announcement in time *t*; otherwise, it equals to zero. ES_{jt} is computed using analysts' consensus forecast and scaled by the beginning stock price.
FD_t	An indicator variable for the post Regulation Fair Disclosure period that takes the value of 1 if year *t* is greater than year 2000. Otherwise, it equals zero.
$Firm\_Exp_{ijt}$	The number of years for which an analyst *i* has issued any forecast for firm *j* in the *I/B/E/S* database by year *t*. This variable is a proxy for the analyst's familiarity with the firm.
For_Freq_{ijt}	The number of forecasts analyst *i* makes for a firm during year *t*. This variable is a proxy for the analyst's effort. We count all types of forecasts, such as sales forecasts, earnings forecasts, and for all forecast horizons, such as annual forecasts and quarterly forecasts.
$Follow\_Ind_{ijt}$	An indicator variable that takes the value of 1 if analyst *i* follows at least one firm in the same industry that firm *j* belongs to in year *t*; otherwise, it equals zero.
For_Hor_{ijt}	The number of calendar days between analyst *i*'s forecast date for firm *j*'s earnings in fiscal year *t* and the fiscal-year end date.
$FRCHRZ_{ijkt}$	The number of days between the date of analyst *i*'s forecast revision for supplier firm *j* and the date of customer *k*'s earnings news event. If analyst *i* does not revise her forecast after the earnings news event, $FRCHRZ_{ijt}$ is set equal to the number of days from the customer firm's earnings news event to the supplier firm *j*'s earnings announcement date minus 14.
Gen_Exp_{it}	The number of years (starting from 1981 on *I/B/E/S* and including the current fiscal year *t*) for which analyst *i* has earnings forecasts on *I/B/E/S* by year *t*. It measures an analyst's general experience.
$Ln\_C\_MV_{jkt-1}$	The natural logarithm of the year-end equity market capitalization of firm *j*'s customer *k* in year *t-1* calculated with data obtained from *COMPUSTAT* Database.
$Ln\_Firm\_MV_{jt-1}$	The natural logarithm of the year-end equity market capitalization of firm *j* in year *t-1*.
$N\_OtherAnalyst\_Follow\_C_{ijkt}$	The number of analysts other than analyst *i* following firm *j*'s customer *k* in year *t*.
$N\_OtherAnalyst\_Follow\_Firm_{ijt}$	The number of analysts other than analyst *i* following firm *j* in year *t*.
Num_Firm_{it}	The number of firms covered by analyst *i* in year *t*.
Num_Ind_{it}	The number of I/B/E/S industries (*INDABB*) analyst *i* follows in year *t*.
$PreAFA_{ijkt}$	The absolute value of firm *j*'s actual earnings in time *t* minus the earnings forecast issued by analyst *i* right before customer *k*'s earnings news event date, scaled by firm *j*'s stock price one day before the event day.
RET_{jt}	Market-adjusted return calculated as raw return minus value weighted market index return from CRSP accumulated from analyst *i*'s previous forecast date to the event date, i.e. the customer's earnings announcement date or customer's management forecast date.

Table 1
Number of observations by sample and year
Our initial sample consists of supplier-customer firm pairs in the *COMPUSTAT* Industry Segment Customer file over the period from January 1982 to December 2010. Following the procedure of Fee and Thomas (2004), we use the customer name to manually match the customer to a company on the *COMPUSTAT* Industrial file. If a match is found, we retrieve the corresponding identifier (i.e., GVKEY) of the customer firms. As reported under column (2), this procedure results in 63,589 supplier-customer pairs over the 29-year sample period.

(1)	(2)	(3)	(4)	(5)
Year	Number of supplier-customer pairs	Number of supplier-customer pairs with at least one analyst covering the supplier	Number of analyst-supplier-customer observations	Number of analyst-supplier observations
1982	1,257	229	976	739
1983	1,532	407	3,306	2,263
1984	1,657	540	4,609	2,944
1985	1,872	564	5,302	3,568
1986	2,024	652	6,171	4,169
1987	2,006	717	5,818	4,020
1988	1,930	629	4,746	3,471
1989	1,904	621	5,433	3,964
1990	1,994	671	5,003	3,478
1991	2,147	704	5,227	3,572
1992	2,259	755	5,086	3,574
1993	2,492	919	6,072	4,414
1994	2,556	1,081	6,408	4,596
1995	2,855	1,135	6,654	4,729
1996	2,921	1,402	7,802	5,399
1997	2,649	1,360	7,688	5,436
1998	2,464	1,204	7,182	5,019
1999	1,525	690	4,874	2,754
2000	2,027	1,031	7,876	4,407
2001	2,144	1,086	9,319	5,379
2002	2,432	1,241	12,206	6,233
2003	2,523	1,220	11,166	6,060
2004	2,635	1,351	12,271	6,464
2005	2,611	1,390	12,987	7,145
2006	2,265	1,236	11,736	6,599
2007	2,282	1,346	13,034	7,387
2008	2,219	1,309	12,880	7,360
2009	2,263	1,370	13,334	7,498
2010	2,144	1,352	14,084	7,668
Total	63,589	28,212	229,250	140,309

Table 2
Economic determinants of an analyst's decision to initiate coverage of a covered firm's customer (test of hypothesis H1)

The sample consists of all *I/B/E/S* analysts who follow a supplier company that reports at least one customer firm in the *COMPUSTAT* industry segment customer files over the period from January 1982 to December 2010. There are a total of 132,676 analyst-supplier-customer-year observations with non-missing values for all regression variables: 1,015 observations are with *Follow_C*=1 (in the initiation year only) and 131,661 with *Follow_C*=0 (for all years). Panel A provides descriptive statistics for variables used in testing hypothesis H1. See the data appendix for definitions of the variables. Panel B summarizes the estimation of the economic determinants of an analyst's decision to initiate coverage of a firm's major customer using the Cox's proportional hazard model. Predicted signs of the estimated coefficients are given under column (2). *z*-statistics are calculated using standard errors clustered by analyst and year. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Descriptive statistics on regression variables

(1)	(2) All observations (N=132,676)			(3) *Follow_C*=1 in the initiation year only (N=1,015)			(4) *Follow_C*=0 (N=131,661)		
Variable	Mean	Median	S.D	Mean	Median	S.D	Mean	Median	S.D
C_Sales_{t-1}	0.16	0.13	0.13	0.18	0.15	0.13	0.16***	0.13***	0.13
$Ln\_C\_MV_{t-1}$	9.51	9.76	1.91	9.55	9.95	1.71	9.51	9.76	1.91
C_Volume_{t-1} *(in thousand)*	13,228	4,064	24,515	14,787	4,295	27,927	13,215*	4,064	24,487
$C\_Leverage_{t-1}$	0.24	0.17	0.21	0.25	0.19	0.23	0.24	0.17	0.21
$CS\_in\_SameInd_{jkt}$	0.21	0.00	0.40	0.56	1.00	0.50	0.20***	0.00***	0.40
C_in_CoreInd	0.24	0.00	0.42	0.49	0.00	0.50	0.23***	0.00***	0.42
N_OtherAnalyst_Follow_C	24.58	24.00	13.45	30.49	31.00	12.44	24.53***	24.00***	13.45
$Ln\_Firm\_MV_{t-1}$	6.97	6.90	1.86	7.17	7.07	1.84	6.96***	6.90***	1.86
N_OtherAnalyst_Follow_Firm	15.05	12.00	11.16	17.67	16.00	11.34	15.03***	12.00***	11.15
Gen_Exp	6.31	5.00	5.05	5.56	4.00	4.10	6.32***	5.00***	5.05
Firm_Exp	2.91	2.00	2.64	3.31	2.00	2.23	2.90***	2.00***	2.64
Num_Firm	18.95	16.00	16.99	23.46	18.00	21.75	18.92***	16.00***	16.95
Broker_Size	71.66	51.00	71.79	68.50	53.00	68.59	71.68	51.00	71.81
Broker_Follow_C	0.41	0.00	0.49	0.47	0.00	0.50	0.41***	0.00***	0.49
FD	0.61	1.00	0.49	0.43	0.00	0.50	0.61***	1.00***	0.49

(Continued…)

Table 2 (…continued)

Panel B: Proportional hazard model Unit of analysis: supplier-customer-analyst (N=62,636)

(1) Variables	(2) Pred.	(3) Hazard coeff.	(4) *z-stat*	(5) Hazard Ratio
C_Sales_{t-1}	+	0.850***	3.96	2.339
$Ln\_C\_MV_{t-1}$	?	-0.036	-1.32	0.964
C_Volume_{t-1}	+	0.000***	3.09	1.000
$C\_Leverage_{t-1}$	+	0.466**	2.21	1.593
CS_in_SameInd	+	0.144	1.42	1.155
C_in_CoreInd	+	1.563***	15.44	4.772
N_OtherAnalyst_Follow_C	?	0.019***	5.23	1.019
$Ln\_Firm\_MV_{t-1}$	?	0.217***	6.47	1.242
N_OtherAnalyst_Follow_Firm	+	-0.008*	-1.78	0.992
Gen_Exp	+	-0.053***	-4.79	0.948
Firm_Exp	+	-0.024	-0.90	0.976
Num_Firm	–	0.010***	7.93	1.010
Broker_Size	?	0.001	1.61	1.001
Broker_Follow_C	–	-0.130	-1.53	0.878
FD	?	-0.546*	-1.96	0.579
Wald Chi-square		1265.53		
Year Fixed Effects		YES		
Clustered by		Analyst, Firm		

Table 3

Forecast accuracy and analyst coverage of a supplier firm's major customer (test of hypothesis H2)

The sample consists of all *I/B/E/S* analysts who follow a supplier company that reports at least one major customer firm in the *COMPUSTAT* industry segment customer files over the period from January 1982 to December 2010. The dependent variable, *Accu_Score,* is the relative forecast accuracy of an analyst for a specific supplier firm. See the data appendix for definitions of the other variables. Panel A reports summary statistics on the regression variables used in testing hypothesis H2. There are a total of 117,919 analyst-supplier-year observations, 96,000 with *Dum_Follow_C*=0 and 21,919 with *Dum_Follow_C*=1. *Dum_Follow_C* is an indicator variable that takes the value of one if the analyst follows at least one of the firm's major customers in a particular year; zero otherwise. See the data appendix for definitions of the other variables. Panel B summaries the estimation of equation (2) using the Heckman's (1979) two-stage procedure and the two-stage least-squares (2SLS) method. Predicted signs of the estimated coefficients are given under the "Pred." column. *t*-statistics are calculated using standard errors clustered by analyst and year. The critical values for an *F*-test are 6.63, 3.84, and 2.71 at the 1%, 5%, and 10% levels, respectively. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Descriptive statistics on regression variables

(1)	(2) All observations (N=117,919)			(3) *Dum_Follow_C*=1 (N=21,919)			(4) *Dum_Follow_C*=0 (N=96,000)		
Variable	Mean	Median	S.D.	Mean	Median	S.D.	Mean	Median	S.D.
Accu_Score	50.00	50.00	31.50	50.67	50.00	30.81	49.85***	50.00***	31.66
Dum_Follow_C	0.19	0.00	0.39	1.00	1.00	0.00	0.00	0.00	0.00
Dum_Broker_Follow_C	0.45	0.00	0.50	0.36	0.00	0.48	0.47***	0.00***	0.50
Dum_C_in_CoreInd	0.35	0.00	0.48	0.69	1.00	0.46	0.27***	0.00***	0.44
Dum_CS_in_SameInd	0.37	0.00	0.48	0.61	1.00	0.49	0.31***	0.00***	0.46
Follow_Ind	0.88	1.00	0.32	0.94	1.00	0.24	0.87***	1.00***	0.33
Num_Ind	8.54	7.00	5.80	9.38	8.00	5.91	8.35***	7.00***	5.75
Days_Elap	15.12	6.00	24.98	12.82	6.00	21.26	15.65***	6.00***	25.73
For_Hor	113.08	71.00	81.63	113.15	72.00	79.79	113.07	71.00**	82.04
For_Freq	3.33	3.00	1.99	3.28	3.00	1.92	3.34***	3.00**	2.01
Gen_Exp	6.75	5.00	4.94	7.37	6.00	5.01	6.61***	5.00***	4.91
Firm_Exp	3.36	2.00	2.78	3.75	3.00	2.94	3.27***	2.00***	2.74
Broker_Size	67.78	50.00	67.23	68.47	53.00	66.69	67.63*	49.00***	67.36
Num_Firm	19.87	17.00	13.50	23.67	19.00	15.43	19.00***	16.00***	12.86
Ln_Firm_MV$_{t-1}$	7.01	6.92	1.78	7.23	7.16	1.72	6.96***	6.87***	1.79
FD	0.50	1.00	0.50	0.39	0.00	0.49	0.53***	1.00***	0.50

(Continued…)

Table 3 (…continued)

Panel B: Forecast accuracy and analyst coverage of a supplier firm's major customer (N=117,919)

(1)	(2)	(3)		(4)	
		Heckman		2SLS	
Explanatory variable	Pred.	Coeff.	t-stat.	Coeff.	t-stat.
Intercept	?	63.14	61.81***	62.55	111.75***
Dum_Follow_C	+	0.92	3.45***	3.62	3.61***
Dum_Broker_Follow_C	+	0.61	2.66***	0.75	3.57***
Dum_C_in_CoreInd	+	-0.39	-1.23	-0.82	-2.28**
Dum_CS_in_SameInd	+	-0.38	-1.73*	-0.41	-1.74*
Follow_Ind	+	1.00	4.07***	0.90	3.11***
Num_Ind	−	-0.05	-1.92*	-0.06	-3.30***
Days_Elap	−	0.03	5.37***	0.03	7.97***
For_Hor	−	-0.12	-32.28***	-0.12	-94.85***
For_Freq	+	0.62	7.03***	0.64	11.89***
Gen_Exp	+	-0.10	-3.30***	-0.10	-4.56***
Firm_Exp	+	0.05	1.13	0.05	1.21
Broker_Size	+	0.00	0.12	0.00	-0.12
Num_Firm	−	-0.02	-1.12	-0.02	-2.86***
Ln_Firm_MV	+	-0.08	-1.23	-0.11	-1.79*
FD	?	-2.10	-4.25***	-2.00	-9.06***
Inverse Mills Ratio	?	-0.39	-1.11		
Adjusted R^2		10.38%		10.36%	
F-statistics (coefficients on Dum_*Follow_C* and *Follow_Ind* are equal)		0.04		6.33**	

Table 4

Analysts' reaction in response to customers' earnings announcement news (tests of hypotheses H3 and H4)

The sample covers the period from January 1982 to December 2010. Panel A presents descriptive statistics on the regression variables. Panel B summarizes the estimation of the logistic regression equations (3a) and (3b). The dependent variable, Dum_REV_{ijkt}, is an indicator variable that takes a value of one if analyst *i* revises her forecast of supplier *j*'s one-year ahead annual earnings within 14 days after its customer *k* releases earnings in time *t*, and zero otherwise. Panel C summarizes the estimation of equations (4a) and (4b). The dependent variable, REV_{ijkt}, is the difference between analyst *i*'s revised and prior forecasts on supplier *j*'s one-year ahead annual earnings, scaled by the stock price of firm *j* a day before the issuance of analyst *i*'s prior forecast. See the data appendix for definitions of the other variables. Predicted signs of the estimated coefficients are given under the "Pred." column. Test statistics are calculated using standard errors clustered by analyst and year. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Summary Statistic

(1)	(2) All observations (N=531,929)			(3) *Follow_C=1* (N=79,318)			(4) *Follow_C=0* (N=452,611)		
Variable	Mean (%)	Median (%)	S.D. (%)	Mean (%)	Median (%)	S.D. (%)	Mean (%)	Median (%)	S.D. (%)
Dum_REV	22.37	0.00	41.68	23.08	0.00	42.14	22.25***	0.00***	41.59
Abs(CES)	0.33	0.10	0.68	0.37	0.12	0.70	0.32***	0.10***	0.67
Abs(ES)	0.11	0.00	0.34	0.13	0.00	0.36	0.11***	0.00***	0.34
Abs(RET)	10.35	6.42	11.27	9.82	6.17	10.70	10.45***	6.47***	11.37
REV	-0.27	0.02	1.90	-0.30	0.02	2.02	-0.26**	0.02	1.88
CES	0.03	0.04	0.75	0.05	0.04	0.80	0.03***	0.04	0.74
ES	0.01	0.00	0.36	0.00	0.00	0.38	0.01***	0.00	0.36
RET	0.33	-0.18	15.30	0.40	-0.06	14.52	0.32	-0.20***	15.44
Follow_C	14.89	0.00	35.60	100.00	100.00	0.00	0.00	0.00	0.00

Panel B: *Logistic regression of Dum_REV on the absolute magnitude of customer's earnings surprises*

(1)		(2) All observations (N=531,929)		(3) *Follow_C=1* (N=79,318)		(4) *Follow_C=0* (N=452,611)	
Variable	Pred.	*Coeff.*	*p-value*	*Coeff.*	*p-value*	*Coeff.*	*p-value*
Intercept	?	-2.309	0.001***	-2.590	0.001***	-2.251	0.001***
Abs(CES)	+	3.381	0.001***	5.551	0.009***	2.940	0.001***
Abs(ES)	+	105.400	0.001***	88.006	0.001***	108.800	0.001***
Abs(RET)	+	1.080	0.001***	1.017	0.001***	1.082	0.001***
Follow_C	?	0.157	0.001***				
Abs(CES) × *Follow_C*	+	-0.245	0.915				
Pseudo R^2		0.061		0.068		0.061	

(Continued…)

Table 4 (…continued)

Panel C: Regression of REV on the earnings surprises of both supplier and customer firms

(1)		(2) All observations (N=531,929)		(3) *Follow_C=1* (N=79,318)		(4) *Follow_C=0* (N=452,611)	
Explanatory variable	Pred.	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Intercept	?	0.000	-0.340	0.001	1.690*	0.000	-0.660
CES	+	0.012	4.460***	0.013	1.780*	0.011	4.360***
ES	+	0.677	38.350***	0.720	18.630***	0.668	35.490***
RET	+	0.003	19.630***	0.005	9.290***	0.003	18.810***
Follow_C	?	0.000	-2.600***				
$CES \times Follow\_C$	+	0.001	0.160				
Adjusted R^2		0.080		0.092		0.078	

Table 5

Improvement in analysts' forecast accuracy in response to customers' earnings announcement news (test of hypothesis H5)

This table summarizes the estimation of equation (5). The sample consists of all *I/B/E/S* analysts who follow a supplier company that reports at least one customer firm in the *COMPUSTAT* industry segment customer files over the period from January 1982 to December 2010. The dependent variable, $ACCIMP_{ijkt}$, is the change in analyst *i*'s forecast error for supplier *j* scaled by firm *j*'s stock price around customer *k*'s earnings news event. See the data appendix for definitions of the other variables. *t*-statistics are calculated using standard errors clustered by analyst. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

(1)	(2)		(3)		(4)	
	90 days window		*60 days window*		*30 days window*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Intercept	1.218	3.500***	1.240	6.220***	1.598	5.530***
Follow_C	0.186	1.990**	0.236	2.090**	0.175	1.570
PreAFA	0.018	1.180	0.011	1.190	0.011	1.080
FRCHRZ	0.001	2.360**	0.000	0.830	0.000	0.060
For_Freq	-0.012	-1.700*	-0.011	-1.380	-0.022	-2.630***
Firm_Exp	0.027	3.780***	0.024	2.900**	0.026	2.440**
Gen_Exp	-0.005	-1.390	-0.002	-0.490	-0.001	-0.120
Broker_Size	0.000	1.410	0.000	-0.120	0.000	1.490
Num_Firm	-0.002	-1.380	-0.004	-2.560**	-0.007	-3.430***
Num_Ind	0.001	0.220	0.006	1.170	0.006	0.980
N_OtherAnalyst_Follow_Firm	0.005	1.310	0.004	1.140	0.007	1.560
lag_ln_Firm_MV	-0.270	-7.550***	-0.236	-6.260***	-0.288	-5.600***
Year Fixed Effects	YES		YES		YES	
N	98,217		55,031		32,405	
Adjusted R^2	0.014		0.012		0.016	

Europe Campus
Boulevard de Constance
77305 Fontainebleau Cedex, France
Tel: +33 (0)1 60 72 40 00
Fax: +33 (0)1 60 74 55 00/01

Asia Campus
1 Ayer Rajah Avenue, Singapore 138676
Tel: +65 67 99 53 88
Fax: +65 67 99 53 99

Abu Dhabi Campus
Muroor Road - Street No 4
P.O. Box 48049
Abu Dhabi, United Arab Emirates
Tel: +971 2 651 5200
Fax: +971 2 443 9461

www.insead.edu

INSEAD

The Business School
for the World®

Printed by INSEAD