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Franco Wong
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will present

"Analyst Following Along the Supply Chain"

on

January 13, 2012

1:30pm in BA 286

Analyst Following Along the Supply Chain*

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October 6, 2011

Comments Welcome.

* We thank Ling Cen, Peter Kennedy, Stan Markov, Suresh Radhakrishnan, Sundaresh Ramnath, Gord Richardson, Tjomme Rusticus, Ram Venkataraman, Peter Wysocki, and workshop participants at the City University of Hong Kong, the 10th Anniversary London Business School Accounting Symposium, the University of Miami, and the 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 and the Social Sciences and Humanities Research Council of Canada.

Analyst Following Along the Supply Chain

Abstract

This study investigates the determinants and consequences of analysts strategically following the major customers of the firms in their research portfolios. We find that the likelihood of an analyst following a firm's major customers increases with the strength of the economic ties along the supply chain, as measured by the percent of the firm's sales to those customers. This result is consistent with these analysts understanding the informational complementarities between the firm and its customers. Moreover, we show that analysts who follow a firm's major customers incorporate the customers' earnings news into their forecast revisions for the supplier firm, but other analysts do not. In contrast, analysts who do not cover a firm's major customers are slow in responding to revisions in the customers' consensus forecasts. Finally, our evidence suggests that analysts who follow their major customers provide more accurate earnings forecast for the supplier firms, and that the greater forecast accuracy attributed to following a firm's major customers is as large as the effect of following the firm's industry peers.

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

JEL Classification: D80; G14; M41

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 major 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 the suppliers' stock prices in various settings.

Given the economic bonds and informational complementarities between the firms along the supply chain, we expect equity market participants to take into account the supplier and customer relation and explore the information transfers along the supply chain. We conjecture that the gathering and processing of information about a firm's major customers by analysts facilitate the incorporation of customer information into the stock price of the supplier firm. In this paper, we examine the economic determinants and consequences of equity analysts covering the major customers of the firms in their research portfolios.

Using a sample of firms with supplier-customer relations over the period from 1982 to 2008, we document five key results. First, we find that the likelihood of an analyst covering a firm's major customer is positively related to the strength of the economic link between the customer and supplier firms, which we measure as the percent of a firm's sales to that customer. Hence, the strength of the economic bond between the trading partners is an important consideration for analysts to follow a firm's major customers. Second, analysts who follow their portfolio firms' customers incorporate the earnings news of the customers into their revisions of the suppliers' earnings, but other analysts do not. In particular, the probability of the former analysts issuing a forecast revision for the suppliers within 14 days of their customers' earnings releases increases with the absolute magnitude of the earnings news. Moreover, the forecast revisions of the suppliers' earnings are positively associated with the magnitude of the customers' earnings surprises. Third, analysts who do not cover a firm's major customers respond slowly to the revisions of consensus forecasts of the customers' earnings. Fourth, analysts who cover a firm's major customers provide more accurate earnings forecasts for the firm, controlling for other well-known determinants of forecast accuracy. Finally, analyst forecast performance benefits as much from following a firm's major customers as from covering the firm's industry peers.

This study is related to several strands of literature in accounting. 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; Kini et al. (2009) argue that it can be beneficial to expose analysts to alternative sources of complementary information.[1] We add to this line of research by documenting that some analysts cover firms from different industries in order to explore informational complementarities between firms along the supply chain.

[1] Kini et al. (2009) examine the conditions under which analysts cover firms in a single country versus multiple countries. Sonney (2009) examines the benefits of industry specialization versus country specialization.

Second, previous studies have documented results consistent with the existence of vertical information transfers 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 major customers, and examine the cross-sectional variation of the market reactions. In this study, we investigate analysts' strategic use of the information complementarities between firms along the supply chain. While the aforementioned studies examine investor reactions to news about a firm's major customers, we focus on the responses of analysts and find that analysts who follow the customer firms incorporate the earnings news of the customers into the revisions of their earnings forecasts for the suppliers. Hence, we provide evidence for the mechanism by which customer firms' earnings news is impounded into their suppliers' stock prices.[2]

Third, Cohen and Frazzini (2008b) document that the consensus forecast revisions for suppliers are predictable using the lagged customer forecast revisions, and they attribute the delay to analyst inattention.[3] In this study, we find that analysts who follow their portfolio firms' customers incorporate the earnings news of the customers into their revisions of the suppliers' earnings, but other analysts do not. We also show that analysts who do not follow a firm's customers lag in their response to revisions of the customers' consensus earnings forecasts, but the same is not true for those analysts who cover both firms. Hence, our results imply that the

[2] We assume that the future cash flows and earnings of a firm are positively correlated with those of its major customers. However, this assumption might not always hold. For example, the growth and expansion of the major 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.

[3] Cohen and Frazzini (2008a) show that customer stock returns predict its supplier's subsequent stock returns. Menzly and Ozbas (2010) report that economically linked industries cross-predict each other's returns, and Shahrur et al. (2009) find similar results using international industry-level data.

anomaly documented in Cohen and Frazzini (2008b) could be due to the lack of analysts following the supplier firms' major customers.

Fourth, we contribute to the literature on the relation between analyst specialization/diversification and analysts' 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 by exposing analysts to alternative sources of complementary information. We provide evidence supporting the argument of Kini et al. (2009). Specifically, we show that analysts covering firms from different industries along the supply chain actually exhibit better forecast accuracy, and the improvement in forecast accuracy is as large as that which comes from following a firm's peers in the same industry.

Overall, our results are consistent with analysts strategically covering the major customers of the firms in their research portfolios, because they can benefit from the information complementarities along the supply chain.[4] Furthermore, since following a firm's major customers indicates that an analyst is well informed about the firm, our paper sheds light on the debate over whether analysts' forecasts are based on firm-specific information as oppose to industry-specific information. When firms have strong economic bonds with their customers, we show that analysts strategically follow the customers to collect firm-specific information on the

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

suppliers. Hence, our evidence is consistent with analysts incorporating firm-specific information into their earnings forecasts.

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 examines the economic determinants of analysts' decisions to cover their portfolio firms' major customers. Section 5 investigates analysts' revisions of supplier firms' earnings in response to the current and lagged earnings news of the firms' customers. Section 6 tests the effect of analyst coverage of customer firms on the accuracy of their earnings forecasts for the corresponding supplier firms. Section 7 concludes.

2. Background and Hypotheses

2.1. Determinants of an analyst's choice to follow a firm's major customer

Analysts strategically construct their coverage portfolios based upon an evaluation of the costs and benefits of covering a firm. The payoffs for the analysts' coverage come from the sales of their research and the trading commissions that the analysts generate for their brokerage houses (Hayes 1998; Gilson et al. 2001). Hence, the analysts might strategically construct the portfolio of firms they follow to enhance the quality and investment value of the research they produce.

Prior research shows that analysts tend to specialize in a few industries (e.g., Gilson et al. 2001; Piotroski and Roulstone 2004; Boni and Womack 2006; 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. Consistent with this information efficiency (or economy of scale) hypothesis, analysts focus their coverage more on a sector as sector-based commonalities increase (Kini et al. 2009). On the other hand, prior research (e.g., Clement and Tse 2005; Boni and Womack 2006; Sonney 2009) has documented that analysts frequently cover multiple sectors. While a diversified portfolio may cause a loss of scale economies, Kini et al. (2009) argue and show that it can potentially improve forecast accuracy by exposing analysts to alternative sources of complementary information.

It is important 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. Studying the major 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 in the same supply chain are influenced by some common factors, such as price, supply/demand, or technological shocks. Hence, following a firm's customers can benefit the analyst by exploiting the vertical information transfer along the supply chain (Pandit et al. 2011). The information that the analyst obtains about the customer firms will provide useful indicators for the corresponding suppliers.

We expect the information complementarity to be greater when there are strong economic ties 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 major customer. Hence, the marginal benefit of including a customer in the coverage portfolio increases with the economic importance of the customer to the supplier. When such marginal benefit (due to information complementarity) exceeds the marginal cost (attributed to loss of economy scale), analysts choose to include the customers in their research portfolios. This discussion leads to our first testable hypothesis (in alternative form):

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

2.2. Analyst's revision of supplier's forecast in response to the customer's earnings news

Information spillovers among firms in the same industry have been widely studied. Foster (1981) and Han and Wild (1990) show that the earnings news of one firm affects the stock prices of other firms in the same industry. Ramnath (2002) finds that the earnings surprises of the first earnings announcers are informative for the earnings news of subsequent announcers in the same industry. However, both analysts and investors underreact to the earnings news of the first announcers. Finally, Thomas and Zhang (2008) document evidence consistent with the late announcers overreacting to the early announcers' earnings news.

Olsen and Dietrich (1985) and Pandit et al. (2011) extend the intra-industry information transfer literature by examining information transfers 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. 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. They further find that the information transfer is due to both changes in the market's expectation of the supplier's future cash flow and changes in market uncertainty.

Moreover, Hertzel et al. (2008) find negative stock returns for the suppliers of firms that filed for bankruptcy. Cohen and Frazzini (2008a, 2008b) and Menzly and Ozbas (2010) document that the stock prices of supplier firms are slow to incorporate the news reflected in their customers' stock prices and analysts' forecast revisions, leading to predictable supplier returns in the subsequent period (the so-called "customer momentum" anomaly). Shahrur et al. (2009) find similar results using international industry-level data, showing that the returns of the customer industries lead the returns of the supplier industries.

In sum, similar to the intra-industry information transfer phenomenon, the earnings news of a customer firm is informative about its suppliers' earnings and, hence, stock prices. Put differently, information spillovers along the supply chain exist, even though investors might be slow in impounding the information into the stock prices of supplier firms.

If analysts strategically cover a firm's major customers, we expect them to pay close attention to the information complementarities between customers and suppliers.[5] Specifically, an analyst should review his or her forecast of the suppliers' earnings in response to news about its customers' earnings. If necessary, the analyst should issue forecast revisions for the supplier and the revision of the supplier's earnings forecast should be related to the customer's earnings news. We state these two testable hypotheses (in alternative form) as follows:

H2a: Ceteris paribus, the larger the absolute magnitude of a customer's earnings news, the more likely an analyst will revise her earnings forecast for the supplier firm.

H2b: Ceteris paribus, the analyst's earnings forecast revision of the supplier firm is positively associated with the earnings news of the customer firm.

We further conjecture that the analysts who cover a firm's major customer would pay more attention to the customer's earnings news than those analysts who do not. Hence, we test two additional hypotheses (in alternative form) as follows:

H2c: Ceteris paribus, the relation between the absolute magnitude of a customer's earnings news and the likelihood for an analyst to revise her earnings forecast for the supplier firm is stronger for analysts who cover the customer firm.

[5] In fact, Cohen and Frazzini (2008a) attribute the customer momentum anomaly to investor inattention.

H2d: Ceteris paribus, the relation between analyst's earnings forecast revision of the supplier firm and the earnings news of the customer firm is stronger for analysts who cover the customer firm.

2.3. Analyst's coverage of customer firm and forecast accuracy

Prior studies have provided several determinants of 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), and an analyst's portfolio choices (Clement 1999; Kini et al. 2009; Sonney 2009).

Regarding an analyst's portfolio choices, the prior literature shows that analysts can enjoy economies of scale in information acquisition and production by specializing in one industry (Clement 1999). However, Kini et al. (2009) argue and find that the relation between sector diversification and forecast accuracy is unclear. This is because analysts can also benefit from the information complementarities among firms from different sectors or countries that are exposed to similar risk factors. Hence, the impact of analyst portfolio choice on forecast accuracy is thus a result of the tradeoff between these two competing forces.

Given a strong economic link between customer and supplier firms, an analyst is expected to enjoy an information advantage from covering firms along a supply chain. The information gathered for one firm can have implications for another firm. On the other hand, following a firm's customer may 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. For example, both Clement (1999) and Kini et al. (2009) find for U.S. firms a negative relation between analyst forecast accuracy and the number of industries/sectors an analyst follows. If the economic links between customers and suppliers are strong, we expect the information complementarity effect to dominate the loss of scale economies. We thus expect that analysts who cover a firm's major customer firm(s) to provide more accurate earnings forecasts. Formally, we propose the following hypothesis (in alternative form):

H3: Ceteris paribus, analysts who cover a firm's major customer(s) provide more accurate earnings forecast for a supplier firm compared with those who do not.

3. Sample and Data

Our initial sample consists of supplier-customer firm pairs over the period from January 1982 to December 2008. *SFAS Nos*. 14 and 131 require firms to disclose the identity of any customer representing more than 10% of the firm's total sales.[6] We retrieve the names of the major 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 company on the *COMPUSTAT* Industrial file. If a match is found, we retrieve the corresponding identifiers, i.e., GVKEY of the customer firms, from the *COMPUSTAT* Industrial file. This results in 39,898 supplier-customer pairs during the 27-year sample period. In comparison, Cohen and Frazzini (2008) identified 30,622 pairs over the period from 1980 through 2004. Table 1, column (2) presents the number of supplier-customer pairs in our sample by year. The number increases gradually since 1982 and peaks at 2,154 pairs in 1996.

To test hypothesis *H1* regarding the analyst's decision to follow the major customer of a firm in her coverage portfolio, we start with a sample of analysts who followed the supplier firm

[6] 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.

of each supplier-customer pair in each year. Column (3) in table 1 indicates that there are a total of 28,239 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 large number (260,371) of analyst-supplier-customer-year observations (column 4 in table 1). This is the sample we use to test hypothesis *H1* (the actual number of observations used is lower because of missing data for some of the control variables).

The examination of hypotheses *H2a – H2d* starts with the sample used to test hypothesis *H1*. From within this sample, we include all observations with an earnings news event from the customer firm. Earnings news events include both earnings announcements (quarterly or annual) and analysts' earnings forecast revisions.

To test hypothesis *H3* regarding the impact of following a firm's customer 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 number of analyst-supplier-year observations is 161,345 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 H3 is reduced due to missing data for some of the control variables and the restriction that at least two analysts cover the supplier firm.

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 construction of all the regression variables are described in the subsequent sections and summarized in an appendix.

4. Analyst's Propensity to Cover a Firm's Major Customer

4.1. Research design

We use the following logistic regression model to investigate the economic determinants of an analyst's decision to follow a firm's major customer (hypothesis *H1*):

$$
\begin{aligned}
Prob(Follow\_C_{ijkt}=1) = {} & \beta_0 + \beta_1 C\_Sale_{jkt} + \beta_2 Lag\_Follow\_C_{ijkt} \\
& + \beta_3 Ln\_C\_MV_{jkt} + \beta_4 C\_Vol_{jkt} + \beta_5 C\_Leverage_{jkt} + \beta_6 C\_in\_CoreInd_{jkt} \\
& + \beta_7 N\_OtherAnalyst\_Follow\_C_{ijkt} + \beta_8 Ln\_Firm\_MV_{jt} \\
& + \beta_9 N\_OtherAnalyst\_Follow\_Firm_{ijt} + \beta_{10} Gen\_Exp_{it} + \beta_{11} Firm\_Exp_{ijt} \\
& + \beta_{12} Num\_Firm_{it} + \beta_{13} Broker\_Size_{it} + \beta_{14}\, Broker\_Follow\_C_{ijkt} + \varepsilon_{ijkt}\ , \qquad (1)
\end{aligned}
$$

where the dependent variable, $Follow\_C_{ijkt}$ is an indicator variable that takes a value of one if analyst *i* who follows firm *j* also covers firm *j*'s major customer *k* in year *t*, and zero otherwise. We estimate equation (1) using a sample of *I/B/E/S* analysts who cover the supplier firms in all the supplier-customer firm pairs. Hence, the unit of analysis is the analyst-supplier-customer-year.

As stated in *H1*, we expect that the likelihood of an analyst covering a firm's customer increases with the importance of that customer. We use C_Sales_{jkt} as a proxy for the importance of the economic link between the firm and its customer firm *k*, where C_Sales_{jkt} is defined as the percentage of firm *j*'s sales to its customer *k* in year *t*. *H1* predicts that the more important is customer *k*, the more likely that the analyst will strategically choose to cover firm *k*. Therefore, we expect the estimated coefficient on C_Sales_{jkt} to be positive.

If an analyst has already followed a firm's customer last year, it is more likely that she will continue covering it this year. We control for $Lag\_Follow\_C_{ijkt}$, which is the lag of $Follow\_C_{ijkt}$, to take into account the serial correlation in analyst coverage. We expect a positive coefficient on $Lag\_Follow\_C_{ijkt}$.

We include a number of variables to control for the potential impact of the customer firm's characteristics on the analyst's likelihood of covering that firm. $Ln\_C\_MV_{jkt}$ is the natural logarithm of the equity market capitalization of firm *j*'s customer firm *k* in year *t* at year-end. 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 is more likely 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 them more costly for the analyst to cover. On the other hand, large firms usually provide more public disclosure and thus lead to less costly information acquisition. Therefore, it is unclear how the size of the customer firm would affect the likelihood that the analyst will cover it. Following Barth et al. (2001), we define C_Volume_{jkt} as the annual trading volume of firm *j*'s customer *k* in year *t*, *measured in thousands of shares*. The analyst is more likely to follow stocks with high trading volume, because they help sell her research and generate trading commissions for her brokerage house. $C\_Leverage_{jkt}$ is the leverage of firm *j*'s customer *k* in year *t*, defined as *k*'s total liabilities divided by the market value of equity. High leverage firms may have a greater demand to access the equity markets, thus generating greater need for analyst following. $C\_in\_CoreInd_{ijkt}$ 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 companies 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 follows 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 predict the sign of the coefficient on $N\_OtherAnalyst\_Follow\_C_{ijkt}$.

We also include several variables to control for the characteristics of supplier firm *j*. $Ln\_Firm\_MV_{jt}$ is the market value of firm *j*, measured as the natural logarithm of the equity market capitalization of the firm in year *t*. 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 trading commission revenue) for the analyst to enhance her research by covering its major customers. On the other hand, large supplier firms tend to have rich information environments, making it less important for the analyst to search for more information on their customers. Hence, we do not predict the effect of $Ln\_Firm\_MV_{jt}$ 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 is more likely that an analyst who is covering firm *j*'s customers will have a competitive advantage over other analysts following the same firm.

Last, we control for analyst characteristics that have been shown to affect portfolio choices (Kini et al. 2009). Gen_Exp_{it} is analyst *i*'s general forecasting experience, measured by the number of years since she issued her first earnings forecast in year *t* according to *I/B/E/S* database beginning in year 1982. We expect that a more experienced analyst is more likely to cover customer firms, 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 an earnings forecast for firm *j* in 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 major 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. Following the customer firm is a way for her to enhance her research on the supplier firm. 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. Hence, we expect the estimated coefficient on $Broker\_Follow\_C_{ijkt}$ to be negative.

4.2. Empirical results for analysts' propensity to follow a firm's major customer

Table 2 presents the summary statistics for the variables employed in analyzing the determinants of an analyst's coverage of a firm's customers (hypothesis *H1*). The descriptive statistics are provided for the overall sample, subsample *Follow_C*=0, which are analysts that do not follow a firm's customer in a supplier-customer pair in a particular year, and subsample *Follow_C*=1, which are analysts that follow a firm's customer in a supplier-customer pair in a particular year. There are a total of 182,176 useable analyst-supplier-customer-year observations over the period 1982–2008, 155,698 with *Follow_C*=0 and 26,478 with *Follow_C*=1. In other words, 14.5% of the total observations have an analyst following both the supplier and customer firms.

As shown in the table, mean *C_Sales* is slightly larger in the *Follow_C*=1 subsample than in the *Follow_C*=0 subsample (17.5% versus 16.7%, t-stat = -9.39). The customer firms in these two subsamples are similar in size, *Ln_C_MV*, trading volume, *C_Volume*, and leverage, *C_Leverage*. However, compared with the *Follow_C*=0 subsample, the customer firms in the *Follow_C*=1 subsample are more likely to be in the core industry of the analyst, *C_in_CoreInd*, and have more analysts following them, *N_OtherAnalyst_Follow_C*. Moreover, the supplier firms in the *Follow_C*=1 subsample are larger and have more analysts following them than their counterparts in the *Follow_C*=0 subsample. Finally, the analysts in the *Follow_C*=1 sample have more general and specific experiences, cover more companies, and are from smaller brokerage houses than the analysts in the *Follow_C*=0 sample. Untabulated findings show that *C_Sales* is significantly correlated with many of these explanatory variables, suggesting that controlling for these other factors in the regression is important to disentangle the incremental effect of *C_Sales*.

Table 3 presents the logistic regression results for the analysis of the determinants of an analyst's decision to follow a firm's major customer. Since the unit of analysis is the analyst-supplier-customer-year, we cluster the standard errors by analyst and year. Our main variable of interest is *C_Sales*. Consistent with our prediction, columns (3) shows that the estimated coefficients on *C_Sales* is statistically positive, indicating that the stronger the economic link between the supplier and the customer, the more likely that the analyst will include the customer firm in her portfolio. The specification reported under column (4) takes into account the effect of Regulation Fair Disclosure (Reg FD), which became effective on October 23, 2000. If Reg FD reduces the ability of analysts to collect private information from management (Markov and Gintschel 2004), we expect them to cover the customer firm as a way to replace the loss of information. The statistically positive coefficient on $FD \times C\_Sales$ is consistent with this interpretation.

The result for *C_Sales* is obtained after controlling for various well-known determinants of analyst coverage. The highly significant coefficient on *Lag_Follow_C* is consistent with the fact that an analyst is likely to continue covering the firms that are already in her portfolio. The negative coefficient on *Ln_C_MV* suggests that the analyst is less likely to cover large customer firms, probably due to a low net benefit of doing so. The trading volume and leverage (*C_Volume* and *C_Leverage*) of the customer exhibit an insignificant impact on the analysts' propensity to cover the customer firm. 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. Finally, the positive coefficient on *N_OtherAnalyst_Follow_C* suggests that the more other analysts follow the customer firm, the more likely it is that the analyst will also cover the customer firm.

We find that the characteristics of the supplier firm also affect whether the analyst covers the supplier's major 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 major customer of 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 that has a large analyst coverage.

This result is inconsistent with this variable capturing the competitive reason for the analyst to also follow the customer firm.

Regarding the effect of analyst characteristics on the decision to cover a firm's major customer, the results show that the analyst with more general experience is more likely to cover the customer firm, as shown by the positive coefficient on *Gen_Exp*. Probably the experienced analyst has previous exposure to the customer firm or the related industry, making the marginal cost of following the customer firm low. On the other hand, the estimated coefficient on *Firm_Exp* is statistically negative, indicating that the longer the analyst has followed a firm, the less likely she will include its major customer in her portfolio. This result is opposite to what we predicted. We find a statistically positive coefficient on *Broker_Size*, suggesting that an analyst from a larger brokerage firm has better resources to conduct thorough research on the firms she covers, and can more easily include the firms' major customers in her portfolio. As expected, the estimated coefficient on *Broker_Follow_C* is significantly negative. In other words, when there are other analysts in the same brokerage firm following the customer firm, the analyst is less likely to cover it herself, probably because she can obtain private information about the customer firm from her colleagues directly. In general, these findings are consistent with those documented in Kini et al. (2009).

5. Analysts' Forecast Revisions in Response to the Earnings News of a Firm's Customer

5.1. Research design

The results documented in section 4 are consistent with analysts strategically consider the strength of the economic link between the major customer(s) and the supplier firm when making their coverage choices. To obtain further evidence that analysts explore information about a firm's major customers, we investigate whether analysts revise their earnings forecasts of the firm in response to the customer's earnings news (hypotheses *H2a* and *H2b*). We further expect analysts who cover the customer firm to use the customer earnings news to a greater extent than those who do not when updating their earnings forecasts (hypotheses *H2c* and *H2d*).

First, we use the following logistic regression model (2a) to test the propensity of an analyst to revise her earnings forecast for the supplier firm in response to the earnings news of the customer firm (hypothesis *H2a*):

$$Prob(Dum\_REV_{ijkt}=1) = \beta_0 + \beta_1\, Abs(CES_{kt}) + \beta_2\, Abs(ES_{jt}) + \varepsilon_{ijkt}\ , \tag{2a}$$

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. CES_{kt} is the earnings surprise of customer *k*, computed using analyst *i*'s forecast and scaled by firm *k*'s beginning stock price. ES_{jt} is the earnings surprise of the supplier firm *j* at its most recent earnings announcement, computed using consensus forecast and scaled by firm *j*'s beginning stock price. *Abs(.)* is the absolute value operator. 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.

Second, conditional on analyst *i* making a forecast revision for supplier *j*, we examine the extent to which she revises her earnings forecast in response to the earnings news of customer *k* (hypothesis *H2b*). The regression model is specified as follows:

$$REV_{ijt} = \chi_0 + \chi_1\, CES_{kt} + \chi_2\, ES_{jt} + \chi_3\, Inverse\ Mill's\ Ratio_{ijt} + \nu_{ijt}\ , \tag{2b}$$

where REV_{ijt} is analyst *i*'s revision of supplier *j*'s earnings within 14 days after customer *k*'s earnings announcement in 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} and ES_{jt} are defined as in equation (2a) above. Given the economic link between firms along the supply chain, we expect a positive coefficient on CES_{kt} if analyst *i* uses the earnings news of the customer firm *k* to update her earnings forecasts of the supplier firm *j*. We expect the coefficient on ES_{jt} to be positive; i.e., analysts use the earnings news released by a firm to update their forecasts for the firm.

Since the sample used in this analysis is conditional on those observations with analyst forecast revisions for the supplier firms, we use Heckman's (1979) two-stage procedure to estimate equation (2b). The first stage of the procedure is the logistic regression in equation (2a). In the second stage, the Inverse Mill's ratio, computed from the logistic estimates, is included in equation (2b).

In order to test hypotheses *H2c* and *H2d*, we include $Follow\_C_{ijkt}$ and an interaction term $Abs(CES_{kt})*Follow\_C_{ijkt}$ into equations (2a) and (2b) as follows:

$$Prob(Dum\_REV_{ijkt}=1) = \beta_0 + \beta_1 Abs(CES_{kt}) + \beta_2 Abs(ES_{jt}) + \beta_3 Follow\_C_{ijkt} + \beta_4 Abs(CES_{kt})* Follow\_C_{ijkt} + \varepsilon_{ijkt}\ , \tag{2c}$$

$$REV_{ijt} = \chi_0 + \chi_1 CES_{kt} + \chi_2 ES_{jt} + \chi_3 Follow\_C_{ijkt} + \chi_4 CES_{kt}* Follow\_C_{ijkt} + \chi_5 Inverse\ Mill's\ Ratio_{ijt} + v_{ijt}\ . \tag{2d}$$

A positive estimated coefficient on the interaction term in equations (2c) and (2d) is consistent with hypothesis *H2c* and *H2d*, respectively.

5.2. Empirical findings

5.2.1. Analysts' responses to the earnings news of a firm's major customer

Table 4 presents the results of examining the propensity of an analyst to revise her forecast for the supplier firm in response to the customer firm's earnings surprise (*CES*). There are a total of 86,682 customers' earnings announcements (quarterly and annually) with available data for all regression variables. Panel A reports that 13.4% 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, compared with 11.6% for those who do not (i.e., those in the *Follow_C*=0 subsample).[7] The absolute magnitude of the customers' earnings surprises, *Abs(CES)*, is slightly larger in the *Follow_C=1* subsample than in the *Follow_C=0* subsample. In contrast, the *Follow_C=1* subsample exhibits a smaller $Abs(ES_{jt})$ than the *Follow_C=0* subsample.

Panel B in table 4 summarizes the estimation of equation (2a). In the *Follow_C=1* subsample, the estimated coefficient on $Abs(CES_{kt})$ is significantly positive, suggesting that the larger the magnitude of the customer's earnings surprise, the more likely the analyst will revise her forecast of the supplier's one-year ahead earnings. This result suggests that those analysts who follow a firm's major customer incorporate the earning news of the customer when deciding to update their earnings forecasts for the supplier (hypothesis *H2a*). On the other hand , $Abs(CES_{kt})$ exhibits an insignificant association with *Dum_REV* in the *Follow_C=0* subsample.

[7] If we change the event window from 14 to seven trading days, the results reported in table 4 and table 5 (below) are qualitlatively similar to those reported here.

This finding is consistent with analysts who do not cover their portfolio firms' major customers ignoring the earnings news of the customers when making their forecast revision decisions.[8]

Next, we test whether the analysts from the two subsamples react differently to $Abs(CES_{kt})$ by estimating model (2c) on the full sample. The estimation result is reported in the last column of Panel B in table 4. The statistically positive coefficient on the interaction term, $Abs(CES) \times Follow\_C$, indicates that analysts following the supplier-customer firm pair are more likely to react to the earnings news of the customer when making their forecast revision decisions for the supplier than do analysts who do not follow the customers. This result lends support to hypothesis *H2c*.

Table 5 examines the extent to which analysts revise their forecasts for suppliers in response to the earnings releases of customer firms, conditional on a sample of 99,366 observations in which analysts revised their forecasts of the supplier firms within 14 days after the customers' earnings announcements. Panel A shows that the two subsamples are very similar. In particular, mean *REV*, *CES*, and *ES* are, respectively, -0.006, 0.000, and -0.001 for both subsamples.

Panel B of table 5 reports the estimation results of equation (2b). In the $Follow\_C=1$ subsample, both *CES* and *ES* are significantly positively associated with *REV*. Hence, analysts who cover both firms along the supply chain take into consideration the earnings news of the customer firms, when revising their forecasts for the suppliers (hypothesis *H2b*). The same is not true in the $Follow\_C=0$ subsample, however. The estimated coefficient on *CES* is not distinguishable from zero, implying that analysts who do not cover their firms' major customers

[8] Surprisingly, the estimated coefficient on $Abs(ES_{jt})$ is statistically negative with a t-statistic of -5.71. This could be due to the fact that (a) analysts always respond to the earnings announcements of the firms they cover and, hence, the magnitude of the earnings surprises is irrelevant for their decision to issue a revision or not, and (b) large earnings surprises could be attributed to transitory factors that have little implication for future earnings.

fail to impound the earnings news of the customers into their forecast revisions of the suppliers' earnings.

Finally, when we estimate model (2d) using the full sample, the estimated coefficient on the interaction term, $CES \times Follow\_C$, is statistically positive, with a t-statistic of 2.18. Hence, this evidence is consistent with analysts who follow the customer firm using the information in an earnings surprise of the customer to a greater extent than other analysts when revising her forecast of the supplier firm's earnings.

5.2.2. Analysts' delayed responses to the consensus forecast revisions of a firm's customer

Using a sample of firms with supplier-customer relation, Cohen and Frazzini (2008b) find that equity analysts are slow in responding to the earnings forecast revision of a firm's customer. In particular, they show that last month's customer earnings revision predicts this month's revision of the supplier's earnings (even after controlling for the supplier's own lagged revision; i.e., supplier's earnings momentum). They attribute this finding to analyst inattention to the economic link between a firm and its major customer.

If the finding on analyst's delayed response is attributed to analyst inattention, we expect it to be more pronounced for analysts who do not cover a firm's major customer and less pronounced for those who cover both the supplier and customer firms. Using the following regression model, we test whether these two types of analysts respond to customer's earnings revision with a delay:

$$
\begin{aligned}
REV_{ijt} = \beta_0 + \beta_1\, LAG\_CREV_{kt} + \beta_2\, LAG\_REV_{jt} \\
+ \beta_3\, Inverse\ Mill's\ Ratio_{ijt} + \varepsilon_{ijt}\ , \qquad (4)
\end{aligned}
$$

where REV_{ijt} is analyst *i*'s revision of supplier *j*'s earnings within 14 days after the earnings announcement of customer *k* in time *t* (i.e., same as the dependent variable in equation 3 above). LAG_CREV_{kt} is the most recent revision in the customer's consensus forecast calculated before customer *k*'s earnings announcement. LAG_REV_{jt} is the most recent revision in supplier *j*'s consensus forecast obtained before the customer's earning announcement. The Inverse Mill's ratio is computed from the logistic estimates of equation (2a). Equation (4) is estimated using the same sample used in the estimation of equation (2b) above.

Table 6 summarizes the estimation results by *Follow_C*. Panel A shows that the means and standard deviations of the dependent and explanatory variables are almost identical across the two subsamples, indicating that the two subsamples are similar. Columns (1) and (4) in panel B report the results of replicating a similar regression model used by Cohen and Frazzini (2008b).[9] The results indicate that the lagged revision of the customer's consensus forecast (*LAG_CREV*) exhibits significant explanatory power for current forecast revision of the supplier's earnings made by analysts from both the *Follow_C*=1 and *Follow_C*=0 subsamples. This finding is consistent with Cohen and Frazzini (2008) that analysts are slow in responding to the revision in consensus forecast of a firm's major customer. As in Cohen and Frazzini (2008b), columns (1) and (4) also show that the estimated coefficients on the lagged revision of the supplier's consensus earnings forecast (*LAG_REV*) are significantly positive, suggesting the presence of earnings momentum (Chan et al. 1996).

Columns (2) and (5) show that the current revision in the customer's consensus forecast (*CREV*) also predicts the analyst's forecast revision of the supplier's earnings, after controlling for the supplier's own earnings momentum. Moreover, untabulated statistic indicates that the

[9] Cohen and Frazzini (2008b) conduct their analysis at the supplier-firm level and, hence, their dependent variable is the current consensus forecast revision of the supplier. Our tests are done on analyst-supplier-customer observations and, hence, our dependent variable is an individual analyst's forecast revision of the supplier's earnings.

pair-wise correlation between *LAG_CREV* and *CREV* is over 60% and significant at less than the 1% level (i.e., earnings momentum in customer's earnings). Hence, the ability of *LAG_CREV* to predict an analyst's earnings revision of the supplier could be attributed to its correlation with *CREV*.

To investigate the possibility that the finding in Cohen and Frazzini (2008b) is due to the failure to control for customer earnings momentum, we include both *LAG_CREV* and *CREV* in the regression model. The results are summarized in columns (3) and (6). Specifically, column (3) shows that once *CREV* is controlled for, *LAG_CREV* no longer exhibits significant explanatory power for the current supplier revisions made by analysts in the *Follow_C*=1 subsample. In contrast, column (6) indicates that *LAG_CREV* still predicts subsequent supplier earnings revision made by analysts in the *Follow_C*=0 subsample. In other words, these results are consistent with analysts who do not cover a firm's major customer(s) being slow in incorporating the information in the consensus forecast revision of the customer. However, analysts who follow a firm's major customer(s) do not exhibit a delayed response to the news in the lagged revision in customer consensus forecast.

In sum, our evidence implies that if there are not enough analysts following a firm's major customers, the lagged customer consensus revision will predict the current supplier consensus revision. This evidence provides further support for Cohen and Frazzini's (2008b) conjecture that analyst inattention is a reason for the return predictability across supplier and customer firms documented in Cohen and Frazzini (2008a).

6. Effect of Following Customer Firms on Analyst Forecast Accuracy for Supplier Firms

6.1. Research design

We use the following multiple regression to test hypothesis *H3* that an analyst's covering of a supplier firm's major customers increases her forecast accuracy for the supplier firm:

$$
\begin{aligned}
Accu\_Score_{ijt} = {} & \beta_0 + \beta_1 Dum\_Follow\_C_{ijt} + \beta_2 Broker\_Follow\_C_{ijt} \\
& + \beta_3 C\_in\_CoreInd_{ijt} + \beta_4 Follow\_Ind_{ijt} + \beta_5 Num\_Ind_{it} + \beta_6\, Days\_Elap_{ijt} \\
& + \beta_7\, For\_Hor_{ijt} + \beta_8\, For\_Freq_{ijt} + \beta_9\, Firm\_Exp_{ijt} + \beta_{10}\, Gen\_Exp_{it} \\
& + \beta_{11}\, Broker\_Size_{it} + \beta_{12}\, Num\_Firm_{it} + \beta_{13}\, Ln(Firm\_MV)_{jt} + \varepsilon_{ijt} \qquad (5)
\end{aligned}
$$

The dependent variable, $Accu\_Score_{ijt,}$ is analyst *i*'s accuracy score for firm *j* in year *t*, measuring analyst relative forecast accuracy. Following Hong and Kubik (2003), among others, we calculate the analyst accuracy score as follows:

$$
Accu\_Score_{ijt} = 100 - 100 \times \left\{ \frac{Rank_{ijt} - 1}{NumberFollowing_{jt} - 1} \right\}, \qquad (6)
$$

where $Rank_{ijt}$ is analyst *i*'s forecast accuracy rank for company *j* in year *t,* and $NumberFollowing_{jt}$ is the number of analysts following company *j* in year *t*. Forecast accuracy 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. We estimate equation (5) using a sample of *I/B/E/S* analysts who cover the supplier firms. Hence, the unit of analysis is the analyst-supplier-year.

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 major customer allows the analyst to obtain additional valuable information about the firm's future profitability and leads to greater forecast accuracy (hypothesis *H3*). We thus expect a positive coefficient on *Dum_Follow_C*.

Since there would be information sharing among analysts working in the same brokerage firm, 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 $Broker\_Follow\_C_{ijt}$, which takes the value of one if analyst *i*'s peer at the brokerage firm follows at least one of firm *j*'s customer firms in year *t*, and zero otherwise. The estimated coefficient on $Broker\_Follow\_C_{ijt}$ is expected to be positive. We also conjecture that if the customer firm is in the core industry of analyst *i*, the analyst may acquire relevant information on the customer firm at a lower cost. We capture this construct using $C\_in\_CoreInd_{ijt}$, which takes the value of one if at least one of firm *j*'s customer firms is in analyst *i*'s core industry in year *t*. We expect a positive estimated coefficient on $C\_in\_CoreInd_{ijt}$. Similarly, 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 *CS_in_SameInd*, which takes the value of one if the firm and its customer are in the same industry.

Following prior literature (e.g., Clement and Tse 2005; Kini et al. 2009), we also control for a number of factors that have been shown to affect analyst forecast accuracy. In particular, $Follow\_Ind_{ijt}$ 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*, as it is more efficient for the analyst to follow more than one firm in the same industry. Num_Ind_{it} is the number of 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 fiscal 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 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 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 ($Firm\_Exp_{ijt}$) 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, since resources available to the analyst vary with the size of the brokerage firm. To control for the effort an analyst can expend 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 ($Ln\_Firm\_MV_{jt}$) in our regression.

6.2. Empirical findings on analyst forecast accuracy

In table 7, we present the summary statistics on the variables employed in testing whether covering a firm's major customers results in greater forecast accuracy (hypothesis *H3*). There are 74,456 analyst-supplier-year observations and 20.3% of them have *Dum_Follow_C* equal to one. We separately present the descriptive statistics for the overall sample, subsample with *Dum_Follow_C*=0, and subsample with *Dum_Follow_C*=1. As shown in the table, both the

[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.

mean and median of the *Accu_Score* for subsample with *Dum_Follow_C*=1 are greater than those for the subsample with *Dum_Follow_C*=0. These statistics provide preliminary evidence suggesting that earnings forecasts issued by analysts who follow a firm's major customers are more accurate.

In the *Dum_Follow_C=0* subsample, 50.6% of the analysts have a peer at their brokerage firm who follows at least one of firm *j*'s customer firms (i.e., $Broker\_Follow\_C_{ijt}$ =1), compared with only 40.8% in the *Dum_Follow_C=1* subsample. The average $C\_in\_CoreInd_{ijt}$ value is larger in the *Dum_Follow_C*=1 subsample than in the *Dum_Follow_C*=0 subsample (32.5% versus 12.1%). 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_Hor* for subsample *Dum_Follow_C*=1 is larger than for *Dum_Follow_C*=0, while the mean of *For_Freq* for subsample *Dum_Follow_C*=1 is smaller, suggesting that those analysts who also follow the customer firms update their earnings forecasts for the supplier firms less frequently; these are unexpected results.

Because the individual analyst or her brokerage house decides whether or not to follow a firm's major customer, we use the Heckman's (1979) two-stage procedure to estimate equation (5). In the first stage, we estimate a logistic model similar to the one specified in equation (1). We use analyst-supplier-year observations in this analysis. Hence, if a supplier has more than one major customer, we use the largest customer of the supplier to measure the explanatory variables. The estimation results are stronger than those reported in table 3 and, hence, not tabulated. In the second stage, we include into equation (5) the Inverse Mill's Ratio calculated from the first stage.

The Heckman estimation result is summarized in column (1) of table 8. Consistent with our prediction, the estimated coefficient on *Dum_Follow_C* is positive and statistically significant at the 1% level, with a *t*-statistic of 2.91. This indicates that an analyst who follows a supplier firm's major customers can provide more accurate earnings forecasts for the supplier firm. The positive coefficient on *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 accordingly. Contrary to our expectation, the estimated coefficient on *C_in_CoreInd* is statistically negative. On the other hand, we document a positive and significant coefficient on *Follow_Ind* and a significantly negative coefficient on *Num_Ind*, which is consistent with industry specialization improving forecast accuracy (Clement 1999).

The results on the other control variables are mostly consistent with those documented in prior studies. In particular, the estimated coefficient on *Days_Elap* is negative and significant, suggesting that forecasts clustered together tend to be more accurate (Clement and Tse 2005). 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 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. In contrast to our initial prediction and prior studies, the estimated coefficient on *Broker_Size* is negative although statistically insignificant. The main difference between our test and the others is that we control for *Broker_Follow_C* in the regression. We thus speculate that the main information advantage of working for larger brokerage firms is the access to the information on customer firms. Unlike Clement (1999), we find that portfolio size, *Num_Firm*, has an insignificant effect on analyst forecast accuracy. Last, we find a negative coefficient on *ln_Firm_MV*, suggesting that forecast accuracy is lower for larger firms in general.

We also use the two-stage least squares (2SLS) method to account for endogeneity in the estimation of equation (5). In particular, we use a probit model to estimate the predicted probability of *Dum_Follow_C*. The probit model includes all the explanatory variables in the first-stage of the Heckman procedure discussed above and all the explanatory variables, except the endogeneity variable, in equation (5). In the second stage, we estimate equation (5) 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 (3) in table 8 summarizes the estimation of the second-stage regression. The estimated coefficient on our main variable of interest *Dum_Follow_C* remains positive and significant (*t*-statistics=4.08). The estimation results on the other control variables are qualitatively similar to those in the Heckman regression reported in column (1).

Next, we explore whether Regulation Fair disclosure (Reg FD) influences the effect of coverage of the major customer on an analyst's forecast accuracy. Specifically, we include two additional variables, FD_t and $FD_t \times Dum\_Follow\_C_{ijt,}$ into the model. FD_t is an indicator variable defined as one if year t is 2000 or after, and zero otherwise. The Heckman and 2SLS estimation results are reported in column (2) and (4) respectively. The estimated coefficients on *FD* are statistically negative, suggesting that overall there is a decrease in analyst forecast accuracy in the post-Reg FD period. Nevertheless, the estimated coefficient on the interaction term $FD_t \times Dum\_Follow\_C_{ijt}$ is negative, but indistinguishable from zero. We thus find little evidence that the greater forecast accuracy observed for analysts covering the firm's major customer changes significantly after Reg FD.

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. We document here that the economic link along the supply chain also exposes supplier and customer firms to common shocks. We compare the relative importance of these two economic links by testing the equality of the estimated coefficients on *Follow_Ind* and *Dum_Follow_C* using an *F*-test. The result, reported in the last row of table 8, shows that the two estimated coefficients are not significantly different from each other at the 10% level. In other words, information transfer along the supply chain and intra-industry information transfer have a similar positive effect on analysts' forecast accuracy.

7. Conclusion

This paper examines analysts' portfolio choices along the supply chain. We show that some analysts choose to construct their portfolios along the supply chain, i.e., following both customers and suppliers. Because of the vertical information transfer between customers and suppliers, the more trades between the supplier and customer, the more important they are to each other. Therefore, we find that analysts tend to cover a firm's customers if the firm's sales to that customer account for high percentage of its total sales. Further analyses show that following firms along the supply chain allows the analysts to pay more attention to the earnings news of the customer firms, as well as to utilize such news more efficiently to revise their forecasts of the supplier's earnings. Analysts indeed benefit from the information complementaries between the supplier and customer. In particular, we show that analysts who follow a firm's major customers provide more accurate earnings forecasts for supplier firms. This greater forecast accuracy observed for analysts covering the customer firm is not significantly different from that due to following a firm's industry peers, consistent with analyst forecast performance benefiting as much from covering a firm's customers as from following the firm's peers in the same industry.

References

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.

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

Brown, L.D., 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.

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

Chan, L.K.C., N. Jegadeesh, and J. Lakonishok, 1996. Momentum strategies. Journal of Finance 51(5), 1681-1713.

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.

Cohen, L., Frazzini, A., 2008a. Economic links and predictable returns. Journal of Finance 63, 1977-2011.

Cohen, L., Frazzini, A., 2008b. Economic links and predictable returns: Appendix. Working paper, Harvard University and University of Chicago.

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

Duru, A., Reed, D., 2002. International diversification and analysts' forecast accuracy and bias. Accounting Review 77(2), 415-433.

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.

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.

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

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 University of California at 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.

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 along the supply chain: The economic determinants of suppliers' stock price reaction to their customers' earnings announcements. Contemporary Accounting Research. Forthcoming.

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.

Shahrur, H., Becker, Y. L., Rosenfeld, D., 2009. Return predictability along the supply chain: The international evidence. Working Paper, Bentley University.

Sonney, F., 2009. Financial analysts' performance: Sector versus country specialization. Review of Financial Studies 22, 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. Variables used in testing hypothesis H1 (see section 4)

$Follow\_C_{ijkt}$	An indicator variable for an analyst following a firm's customers. It takes the value of 1, if analyst *i* follows firm *j*'s customer *k* in year *t*. Otherwise, it equals zero.
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*.
$Ln\_C\_MV_{jkt}$	The natural logarithm of the year-end equity market capitalization of firm *j*'s customer *k* in year *t* calculated with data obtained from *CRSP* Database.
$C\_Leverage_{jkt}$	The leverage ratio of firm *j*'s customer *k* in year *t*, *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.
C_Volume_{jkt}	The annual trading volume of firm *j*'s customer *k* in year *t*.
$C\_in\_CoreInd_{ijkt}$	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.
$N\_OtherAnalyst\_Follow\_C_{ijkt}$	The number of analysts other than analyst *i* following firm *j*'s customer *k* in year *t*.
$Ln\_Firm\_MV_{jt}$	The natural logarithm of the average equity market capitalization of firm *j* in year *t*. This variable is a proxy for the firm's information environment.
$N\_OtherAnalyst\_Follow\_Firm_{ijt}$	The number of analysts other than analyst *i* following firm *j* in year *t*.
Gen_Exp_{it}	The number of years (starting from the first year 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.
$Firm\_Exp_{ijt}$	The number of years for which an analyst *i* has issued an earnings 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.
Num_Firm_{it}	The number of firms covered by analyst *i* in year *t*.
$Broker\_Size_{it}$	The number of analysts employed in analyst *i*'s brokerage firm in year *t*.
$Broker\_Follow\_C_{ijkt}$	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.
FD_t	An indicator variable that takes the value of 1 if year t is greater than year 2000. Otherwise, it equals zero.

2. Variables used in testing hypothesis H2 (see section 5)

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_{ijt}	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.
CES_{kt}	Earnings surprise of customer firm *k* at its most recent earnings announcement computed using consensus forecast and scaled by the beginning stock price.
ES_{jt}	Earnings surprise of the supplier firm *j* at its most recent earnings announcement computed using consensus forecast and scaled by the beginning stock price.
LAG_CREV_{kt}	The most recent revision in the customer's consensus forecast made before customer *k*'s earnings announcement.
LAG_REV_{jt}	The most recent revision in supplier *j*'s consensus forecast made before the customer's earning announcement.
$CREV_{kt}$	The current revision in customer *k*'s consensus forecast.

(continued…)

Appendix (…continued)

$Follow\_C_{ijkt}$	An indicator variable for an analyst following a firm's customers. It takes the value of 1, if analyst i follows firm j's customer k in year t. Otherwise, it equals zero.

3. Variables used in testing hypothesis H3 (see section 6)

$Accu\_Score_{ijt}$	$Accu\_Score_{ijt}$ is equal to 100-100* ($Rank_{ijt}$ – 1) /($NumberFollowing_{jt}$ – 1), where $Rank_{ijt}$ is analyst *i*'s accuracy rank for firm *j* in year *t* and $NumberFollowing_{jt}$ is the number of analysts following firm *j* in year *t*. Forecast accuracy 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*.
$Dum\_Follow\_C_{ijt}$	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.
$Broker\_Follow\_C_{ijt}$	An indicator variable that takes the value of 1 if another analyst in analyst *i*'s brokerage house follows at least one of firm *j*'s customers in year *t*; otherwise, it equals zero.
$C\_in\_CoreInd_{ijt}$	An indicator variable that 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.
$CS\_in\_SameInd_{jt}$	An indicator variable that takes the value of 1 if the supplier j and any of the major customer firms are in the same I/B/E/S industry; otherwise, it equals zero.
$Follow\_Ind_{ijt}$	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.
Num_Ind_{it}	The number of industries (INDABB) analyst *i* follows in year *t*.
$Days\_Elap_{ijt}$	The number of calendar days between analyst *i*'s forecast date for the earnings of firm *j* in fiscal year *t* and the previous closest forecast date of any analyst for firm *j* in fiscal year *t*. This variable measures the tendency of forecasts to cluster.
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.
For_Freq_{ijt}	The number of forecasts analyst *i* makes for a firm during fiscal 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 all forecast horizons, such as annual forecasts and quarterly forecasts.
$Firm\_Exp_{ijt}$	The number of years for which analyst *i* has issued an earnings forecast for a firm in the *I/B/E/S* database. This variable is a proxy for the analyst's familiarity with the firm.
Gen_Exp_{it}	The number of years (starting from the first year on *I/B/E/S* and including the current fiscal year) for which analyst *i* has earnings forecasts on *I/B/E/S*. It measures the analyst's general experience.
$Broker\_Size_{it}$	The number of analysts employed in analyst *i*'s brokerage firm.
Num_Firm_{it}	The number of stocks covered by analyst *i* in year *t*. This variable is a proxy for the effort an analyst can expend on following each stock in her portfolio.
$Ln\_Firm\_MV_{jt}$	The natural logarithm of the average equity market capitalization of firm *j* in year *t*. This variable is a proxy for the firm's information environment.
FD_t	An indicator variable that takes the value of 1 if year t is greater than year 2000. Otherwise, it equals zero.

Table 1
Number of observations by sample and year
The sample covers the period from January 1982 to December 2008. We restrict our sample firms to those disclosing major customers in the *Compustat* industry segment customer database and with major customers identifiable in the Compustat Industry File. There are a total of 39,898 supplier-customer pairs and 260,371 analyst-supplier-customer-year observations.

Year (1)	Number of supplier-customer pairs (2)	Number of supplier-customer pairs with at least one analyst covering the supplier (3)	Number of analyst-supplier-customer observations (4)	Number of analyst-supplier observations (5)
1982	625	56	237	147
1983	809	452	3,481	2,292
1984	928	570	5,903	3,711
1985	1,080	633	6,520	4,226
1986	1,166	709	7,081	4,715
1987	1,180	786	7,219	4,850
1988	1,114	733	6,328	4,526
1989	1,131	729	7,079	5,012
1990	1,212	763	7,424	5,002
1991	1,366	875	6,868	4,528
1992	1,494	912	6,480	4,474
1993	1,703	1,148	8,018	5,517
1994	1,810	1,233	8,541	5,960
1995	2,040	1,369	9,410	6,421
1996	2,154	1,602	10,425	6,881
1997	1,979	1,546	10,357	7,249
1998	1,830	1,347	9,739	6,647
1999	1,111	798	6,254	3,550
2000	1,445	1,120	10,200	5,790
2001	1,534	1,181	12,257	7,234
2002	1,732	1,297	15,581	8,312
2003	1,785	1,299	14,772	8,329
2004	1,882	1,374	14,798	8,205
2005	1,851	1,434	15,637	9,168
2006	1,647	1,352	14,782	8,588
2007	1,670	1,467	17,161	9,764
2008	1,620	1,454	17,819	10,247
Total	39,898	28,239	260,371	161,345

Table 2
Descriptive Statistics for variables used in testing hypothesis H1 (N=182,176)
The sample covers the period from January 1982 to December 2008. There are a total of 182,176 analyst-supplier-customer-year observations with non-missing values for all required variables. 155,698 observations are with *Follow_C*=0 and 26,478 with *Follow_C*=1. *Follow_C* is an indicator variable that takes the value of one if the analyst follows a firm's customer in a supplier-customer pair in a particular year; zero otherwise. See the data appendix for definitions of the other variables.

	Overall (N=182,176)		*Follow_C*=0 (N=155,698)		*Follow_C*=1 (N=26,478)	
Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.
C_Sales	0.168	0.134	0.167	0.132	0.175	0.145
Lag_Follow_C	0.090	0.286	0.005	0.072	0.586	0.493
Ln_C_MV	9.571	1.938	9.583	1.974	9.501	1.709
C_Volume (in thousands)	14,794	27,434	14,815	27,441	14,670	27,391
C_Leverage	0.245	0.223	0.242	0.218	0.262	0.250
C_in_CoreInd	0.129	0.335	0.103	0.304	0.281	0.449
N_OtherAnalyst_Follow_C	34.233	17.487	33.478	17.598	38.673	16.118
Ln_Firm_MV	6.824	1.955	6.775	1.956	7.113	1.923
N_OtherAnalyst_Follow_Firm	19.475	15.308	19.091	15.255	21.737	15.421
Gen_Exp	6.421	4.859	6.296	4.854	7.157	4.817
Firm_Exp	3.077	2.691	2.999	2.651	3.529	2.872
Num_Firm	21.610	15.219	20.818	14.698	26.270	17.259
Boker_Size	93.894	97.437	94.361	97.961	91.142	94.255
Broker_Follow_C	0.425	0.494	0.435	0.496	0.370	0.483

Table 3
Economic determinants of an analyst's decision to cover a firm's major customer (N=182,176)
This table summarizes the logistic regression estimation of the economic determinants of an analyst's decision to cover a firm's major customer. 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 2008. The dependent variable, *Follow_C*, is an indicator variable that takes the value of one if the analyst follows a firm's customer in a supplier-customer pair in a particular year; zero otherwise. See the data appendix for definitions of the other variables. Predicted signs of the estimated coefficients are given under column (2). *z*-statistics are calculated using standard errors clustered by analyst and year.

(1)	(2)	(3)		(4)	
Explanatory variables	Pred.	Coefficient	*z-stat*	Coefficient	*z-stat*
Intercept	?	-3.581	-16.28	-3.535	-15.76
C_Sales	+	0.747	4.18	0.504	2.14
Lag_Follow_C	+	5.781	46.44	5.768	45.94
Customer firm characteristics:					
Ln_C_MV	?	-0.205	-7.80	-0.177	-7.51
C_Volume	+	0.000	-1.17	0.000	1.30
C_Leverage	+	0.261	1.52	0.207	1.28
C_in_CoreInd	+	1.108	20.60	1.126	22.24
N_OtherAnalyst_Follow_C	?	0.034	8.65	0.029	7.87
Supplier firm characteristics:					
Ln_Firm_MV	?	0.195	8.68	0.210	9.53
N_OtherAnalyst_Follow_Firm	+	-0.008	-2.37	-0.008	-2.26
Analyst characteristics:					
Gen_Exp	+	0.024	3.54	0.028	4.45
Firm_Exp	+	-0.138	-8.30	-0.140	-8.30
Num_Firm	–	0.018	7.15	0.016	6.52
Broker_Size	+	0.001	1.97	0.001	4.18
Broker_Follow_C	–	-0.395	-3.91	-0.423	-4.13
FD	?			-0.710	-7.74
$FD \times C\_Sales$	+			0.824	2.97
Pseudo R^2		32.20%		32.41%	

Table 4
Analysts' propensity to revise suppliers' earnings forecasts in response to customers' earnings releases
The sample covers the period from January 1982 to December 2008. Panel A presents descriptive statistics on the regression variables. Panel B summarizes the estimation of the logistic regression equation (2). 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. 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.

Panel A: Summary Statistic

Variable	*Follow_C*=1 (N=120,893) Mean	S.D.	*Follow_C*=0 (N=715,023) Mean	S.D.	All observations (N=835,916) Mean	S.D.
Dum_REV	0.134	0.341	0.116	0.321	0.119	0.324
Abs(CES)	0.004	0.010	0.003	0.011	0.004	0.010
Abs(ES)	0.007	0.029	0.009	0.033	0.009	0.032
Follow_C	1.000	0.000	0.000	0.000	0.145	0.352

Panel B: Logistic regression of Dum_REV on absolute magnitudes of customers' and suppliers' earnings surprises

Explanatory variable	Pred.	*Follow_C*=1 (N=120,893) Coeff.	z-stat	*Follow_C*=0 (N=715,023) Coeff.	z-stat	All observations (N=835,916) Coeff.	z-stat
Intercept	?	-1.88	-19.00	-2.01	-23.82	-2.01	-23.80
Abs(CES)	+	6.78	3.40	1.70	1.10	1.67	1.08
Abs(ES)	+	-1.16	-1.72	-2.65	-5.71	-2.43	-5.63
Follow_C	?					0.14	3.04
*Abs(CES)*Follow_C*	+					5.58	2.41
Pseudo R^2		0.07%		0.06%		0.10%	

Table 5

Analysts' revisions of suppliers' earnings forecasts in response to customers' earnings news

The sample covers the period from January 1982 to December 2008. Panel A presents descriptive statistics on the regression variables. Panel B summarizes the estimation of equation (3) using the Heckman two-stage procedure. The dependent variable, REV_{ijt}, 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. The Inverse Mill's Ratio is computed using the logistic estimates of equation (2) reported in table 4. See the 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.

Panel A: Summary Statistics

	Follow_C=1 (N=16,207)		*Follow_C*=0 (N=83,159)		All observations (N=99,366)	
Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.
REV	-0.006	0.033	-0.006	0.033	-0.006	0.033
CES	0.000	0.008	0.000	0.008	0.000	0.008
ES	-0.001	0.018	0.000	0.017	0.000	0.017
Follow_C	1.000	0.000	0.000	0.000	0.163	0.369

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

		Follow_C=1 (N=16,207)		*Follow_C*=0 (N=83,159)		All observations (N=99,366)	
Explanatory variable	Pred.	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Intercept	?	0.18	4.77	0.30	3.03	0.27	3.01
CES	+	0.18	2.22	0.07	1.27	0.06	1.20
ES	+	0.72	7.53	0.50	6.99	0.54	7.77
Follow_C	?					0.00	0.32
CES $\times$ *Follow_C*	+					0.14	2.18
Inverse Mill's Ratio	?	-0.12	-4.85	-0.18	-3.09	-0.16	-3.07
Adjusted R^2		16.97%		7.16%		8.55%	

Table 6
Analysts' delayed response to the customer's consensus forecast revision
The sample covers the period from January 1982 to December 2008. Panel A presents descriptive statistics on the regression variables. Panel B summarizes the estimation of equation (4) using the Heckman's (1979) two-stage procedure. The dependent variable, REV_{ijt}, 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. The Inverse Mill's Ratio is computed using the logistic estimates of equation (2) reported in table 4. See the data appendix for definitions of the other variables. Predicted signs of the estimated coefficients are given under the "Pred." column. Test statistics reported in parentheses are calculated using standard errors clustered by analyst and year.

Panel A: Summary Statistics

Variable	*Follow_C*=1 (N=16,207) Mean	S.D.	*Follow_C*=0 (N=83,159) Mean	S.D.
REV	-0.006	0.033	-0.006	0.033
LAG_CREV	-0.001	0.003	-0.001	0.004
LAG_REV	-0.001	0.007	-0.001	0.008
CREV	0.000	0.003	-0.001	0.004

Panel B: Regression of REV on customer's lagged and current consensus forecast revisions

Explanatory variable	Pred.	*Follow_C*=1 (1)	(2)	(3)	*Follow_C*=0 (4)	(5)	(6)
Intercept	?	0.04	0.04	0.04	0.51	0.51	0.51
		(1.13)	(1.14)	(1.21)	(7.59)	(7.65)	(7.63)
LAG_CREV	+	0.47		0.38	0.30		0.15
		(2.47)		(1.19)	(4.43)		(1.93)
LAG_REV	+	1.07	1.08	1.07	0.70	0.70	0.69
		(6.21)	(5.89)	(6.08)	(5.97)	(6.09)	(5.92)
CREV	+		0.46	0.17		0.36	0.26
			(3.24)	(0.57)		(4.75)	(3.01)
Inverse Mill's Ratio	?	-0.03	-0.03	-0.03	-0.31	-0.31	-0.31
		(-1.26)	(-1.27)	(-1.34)	(-7.67)	(-7.73)	(-7.71)
Adjusted R^2		6.44%	6.29%	6.46%	8.39%	8.41%	8.42%

Table 7
Descriptive Statistics on variables used in testing hypothesis H3
The sample covers the period from January 1982 to December 2008. There are a total of 74,456 analyst-supplier-year observations, 59,368 with *Dum_Follow_C*=0 and 15,088 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.

	Overall (N=74,456)		*Dum_Follow_C*=0 (N = 59,368)		*Dum_Follow_C*=1 (N = 15,088)	
Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.
Accu_Score	50.000	31.514	49.904	31.610	50.379	31.129
Dum_Follow_C	0.203	0.402	0.000	0.000	1.000	0.000
Broker_Follow_C	0.486	0.500	0.506	0.500	0.408	0.491
C_in_CoreInd	0.162	0.369	0.121	0.326	0.325	0.468
Follow_Ind	0.829	0.377	0.814	0.389	0.885	0.320
Num_Ind	9.367	6.520	9.171	6.475	10.141	6.638
Days_Elap	21.145	37.969	21.514	38.562	19.696	35.501
For_Hor	99.839	68.831	99.176	68.539	102.447	69.907
For_Freq	3.762	2.140	3.785	2.162	3.672	2.048
Firm_Exp	3.252	2.783	3.162	2.755	3.603	2.867
Gen_Exp	6.366	4.760	6.225	4.768	6.920	4.689
Broker_Size	94.593	96.733	95.677	97.567	90.328	93.261
Num_Firm	22.765	15.486	21.861	14.828	26.320	17.391
Ln_Firm_MV	7.169	1.846	7.099	1.844	7.445	1.827

Table 8
Forecast accuracy and analyst coverage of a supplier firm's major customer (N=72,750)
This table summarizes the estimation of equation (5) using the Heckman's (1979) two-stage procedure and the two-stage least-squares (2SLS) method. 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 2008. 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. 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.

		(1)		(2)		(3)		(4)	
		Heckman		Heckman		2SLS		2SLS	
Explanatory variable	Pred.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Intercept	?	64.41	59.86	61.48	58.16	61.97	93.17	61.82	80.82
Dum_Follow_C	+	0.97	2.91	0.81	1.73	4.22	4.08	1.49	1.40
Broker_Follow_C	+	0.86	3.10	0.43	1.56	0.86	3.07	0.49	1.79
C_in_CoreInd	+	-1.30	-3.11	-0.22	-0.52	-1.30	-3.56	-0.43	-1.18
CS_in_SameInd	+	-0.18	-0.82	0.01	0.04	-0.11	-0.51	-0.05	-0.25
Follow_Ind	+	0.94	3.98	0.83	3.51	0.85	3.58	0.81	3.43
Num_Ind	–	-0.11	-3.74	-0.11	-3.95	-0.11	-4.03	-0.11	-4.00
Days_Elap	–	-0.03	-7.78	-0.03	-7.94	-0.03	-7.88	-0.03	-8.07
For_Hor	–	-0.11	-19.45	-0.11	-19.88	-0.11	-19.83	-0.11	-20.19
For_Freq	+	0.13	1.82	0.20	2.86	0.15	2.16	0.21	2.89
Firm_Exp	+	0.08	1.49	0.07	1.34	0.09	1.61	0.07	1.29
Gen_Exp	+	-0.07	-1.96	-0.02	-0.71	-0.06	-1.78	-0.03	-0.75
Broker_Size	+	0.00	-0.63	0.00	0.79	0.00	-0.73	0.00	0.83
Num_Firm	–	0.01	0.72	0.00	-0.29	0.00	0.19	0.00	-0.38
ln_Firm_MV	+	-0.11	-1.83	0.07	1.10	-0.11	-1.84	0.05	0.82
FD	?			-2.32	-5.29			-2.14	-4.87
FD $\times$ *Dum_Follow_C*	+			-0.15	-0.27			-0.85	-0.77
Inverse Mill's Ratio		-1.23	-3.29	0.12	0.33				
Adjusted R^2		6.87%		6.97%		6.73%		6.96%	
F-statistics (coefficients on Dum_*Follow_C* and *Follow_Ind* are equal)		0.00		0.01		0.11		0.00	