Title
Risk Pooling, Supply Chain Hierarchy, and Analysts' Forecasts

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Abstract

We investigate whether a firm's risk pooling affects its analysts' forecasts, specifically in terms of forecast accuracy and their use of public vs. private information, and how risk pooling interacts with a firm's position in the supply chain to affect analysts' forecasts. We use a social network analysis method to operationalize risk pooling and supply chain hierarchy and find that risk pooling significantly reduces analysts' forecast errors and increases (decreases) their use of public (private) information. We also find that the positive (negative) relationships between risk pooling and analyst forecast accuracy and analysts' use of public (private) information are more pronounced upstream than downstream in a supply chain.

***Keywords*:** risk pooling, supply chain hierarchy, analyst forecast accuracy, public vs. private information, systematic risk.

Risk Pooling, Supply Chain Hierarchy, and Analysts' Forecasts

1. Introduction

The recent slump in iPhone sales caused a supplier of Apple Inc., Foxconn Technology Group, to report its first-ever annual revenue decline in the past 30 years.[1] Foxconn's first quarter earnings report of 2017 showed that its reliance on iPhone sales resulted in a serious weakness when demand continued to decrease. This suggests that business linkages along supply chains generate significant interdependence between customers and suppliers. Various studies examine such interdependence from the perspective of information transfer. For example, the literature shows that stock prices of suppliers react to the news releases of their customers, indicating that customer information is used by investors to form expectations about the suppliers (e.g., Olsen and Dietrich 1985; Hertzel et al. 2008; Pandit et al. 2011).

However, except for Guan et al. (2015) and Luo and Nagarajan (2015), few studies address how supply chain information (e.g., risk pooling and supply chain hierarchy) affects the behavior (e.g., forecast accuracy) of financial analysts, who are also important but more sophisticated information users.

Risk pooling is widely used in supply chain management to reduce demand variability through diverse customer bases, while supply chain hierarchy influences demand variability due to the demand amplification effect when moving upstream along the supply chain (Forrester 1961). In this study, we first use a social network analysis method to operationalize proxies for customer network structure (e.g., risk pooling) and supply chain hierarchy (Haythornthwaite 1996). We then examine how risk pooling and its interaction with a firm's position in the supply chain hierarchy affect analysts' forecast accuracy and their reliance on public vs. private information.

We hypothesize that risk pooling can increase forecast accuracy through reduced demand variability. The literature shows that demand variability decreases as the number of customers of a firm increases, given that the firm's demand is normally distributed (Dong and Rudi 2004; Berman et al. 2011).

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[1] *https://www.wsj.com/articles/foxconn-reports-first-ever-annual-sales-decline-1490965406*

As the number of customers increases, their demands offset each other and, thus, the aggregated sales variation of the firm decreases. Reduced demand variability helps managers plan production and control costs, reducing earnings volatility and improving the quality of the public information available to analysts and, hence, increases analyst forecast accuracy (Dichev and Tang 2009; Mensah et al. 2004). In addition, as the quality of public information improves, financial analysts may be more likely to rely on public information to make forecasts. Assuming a negative correlation between the precision of public and private information, analysts may rely less on private information when there is higher risk pooling.

The effect of risk pooling on analysts' forecast accuracy and their reliance on public information is subject to the hierarchical position of a firm within the supply chain network. Osadchiy et al. (2015) decompose a firm's total variance of demand into systematic and idiosyncratic risks. Systematic risk is the co-movement of a firm's sales and the market return, while idiosyncratic risk is the firm-specific risk. Risk pooling can reduce the idiosyncratic risk because demands from different customers can offset each other. However, risk pooling cannot reduce the systematic risk. Moving from downstream to upstream, systematic risk increases because it aggregates along the supply chain.[2] Increased systematic risk increases the usefulness of financial analysts' knowledge of the industry and the overall market in making more accurate forecasts and in interpreting firms' public disclosures. Thus, the positive (negative) relationships between risk pooling and analysts' forecast accuracy and their reliance on firms' public (private) information may be more pronounced as firms move from downstream to upstream along the supply chain.

Using publicly listed firms in the U.S. from 2004 to 2010, we find that the larger the number of customers a firm has (our proxy for risk pooling), the smaller the mean analyst forecast error of the firm, and the greater (lesser) the use of public (private) information by analysts. If a manufacturing firm gains one customer, *ceteris paribus*, the absolute mean analyst forecast error relative to the beginning stock price is reduced by 1.12%. Furthermore, the benefit of risk pooling is subject to the supply chain hierarchy. The

[2] Systematic risk usually will not offset as aggregate along the supply chain, because firms of the same supply chain are from related industries and their co-movements with the market may be in the same direction.

positive marginal effect of risk pooling on analyst forecast accuracy and analysts' use of public (private) information increases (decreases) as a firm moves up the supply chain. By gaining one customer, as a firm moves one layer up the supply chain network, the absolute mean analyst forecast error is further reduced by 0.91% times the beginning stock price.

Our study makes the following contributions. First, we contribute to the risk pooling literature, which documents the effect of risk pooling within a supply chain, including lower inventory levels, lower stock-outs, and more manufacturing flexibility. Our study further indicates that risk pooling has an impact on outsiders such as financial analysts. We show that risk pooling increases forecast accuracy through reducing a firm's earnings volatility. In addition, we show that the improved quality of public information resulting from risk pooling encourages analysts to rely more on public information and less on private information. This finding can be useful to both firms and analysts. Public information is free for analysts, so more reliance on public information can reduce their workload when covering a firm and enable them to use their excess capacity to make better forecasts or follow more firms.

Second, Osadchiy et al. (2015) find that systematic risk increases when moving upstream along a supply chain and argue that this may, in turn, increase a firm's cost of capital. We show that the increase in systematic risk enables financial analysts to use their knowledge of the industry and the macro-economy to make more accurate forecasts. Increased forecast accuracy reflects a reduction in information asymmetry between a firm and the financial market and reduces the firm's cost of capital.

Third, our study extends the literature that examines how supply chains affect financial analysts' forecasts. Guan et al. (2015) document that analysts who follow a supplier's customer will produce more accurate forecasts than other analysts due to the benefit derived from informational complementarities between suppliers and customers. In our study we examine how the composition of customers and hierarchical structure of a supply chain network affect analysts' forecasts. We find that risk pooling of customers and the supply chain structure influence analysts' forecast accuracy and their reliance on public (private) information, in addition to the complementarity effect identified by Guan et al. (2015).

Fourth, to the best of our knowledge, this is the first study that uses a social network analysis method to operationalize the proxy of risk pooling and a firm's hierarchical position in the supply chain.

The remainder of our paper is structured as follows. In Section 2 we review the literature and develop research hypotheses. In Section 3 we discuss the methodology. Section 4 reports the empirical results. Section 5 concludes the paper and provides suggestions for future research.

2. Background and Hypotheses Development

2.1. Risk Pooling

Classic inventory theory indicates that higher demand variability leads to higher safety stock and a lower level of customer service. Risk pooling is a technique for reducing demand variability by pooling demand across different individual sources of variation. The equation below shows that the variability of aggregated demand (standard deviation of total demand σ_a) is less than or equal to the sum of the individual variability (sum of standard deviations of demand at the *n* sources).

$$\sum_{i=1}^{n} \sigma_i \geq \sigma_a = \sqrt{\sum_{i=1}^{n} (\sigma_i)^2 + 2\sum_{i=1}^{n} \sum_{i<j}^{n} \sigma_i \sigma_j \rho_{ij}}$$

Cachon and Terwiesch (2006) introduce four risk pooling strategies: location, product, lead-time, and capacity pooling with flexible manufacturing. The location-pooling strategy stores inventory in fewer locations, such as a centralized distribution center, resulting in less inventory holding. The product-pooling strategy serves demand with fewer products, reducing the demand variability of individual products. The lead-time pooling strategy locates a consolidated distribution center between suppliers and retailers, reducing the order lead-time for retailers. Another form of lead-time pooling is delayed differentiation, or a postponement strategy, in which a generic product is initially made and later differentiated into a final form when demand is less uncertain. The capacity pooling strategy suggests a plant produce more than one product with the same capacity, leading to a higher utilization of capacity and a better response to demand uncertainty. In this study, we propose another risk pooling strategy: the number of customers. Dong and Rudi (2004) and Berman et al. (2011) indicate that demand variability is a function of the number of customers. Assuming that demand is normally distributed, as the number of customers (risk pooling) increases, demand variability decreases.

2.2. Risk Pooling and Forecast Accuracy

Risk pooling can improve analyst forecast accuracy in two ways. First, it reduces a firm's earnings volatility. Studies suggest that firms' earnings predictability, determined by their earnings volatility, influences financial analyst forecast accuracy (Mensah et al. 2004; Graham et al. 2005; Dichev and Tang 2009). As the number of customers of a firm increases, their demands offset each other. Thus, the aggregated volatility of the firm's sales decreases. Second, reduced demand variability helps managers plan capacity and production and control costs, leading to a decrease in the volatility of expenses. Therefore earnings, a function of sales and expenses, is likely to have lower volatility and higher predictability as the number of customers increases, leading to higher analyst forecast accuracy. Accordingly, we propose Hypothesis 1A.

Hypothesis 1A: Risk pooling increases analyst forecast accuracy.

2.3. Risk Pooling and Analysts' Use of Public vs. Private Information

The information environment in which analysts operate consists of two elements (Barron et al. 1998): public information and private information. Public information includes common firm-specific information disclosed by firms to all analysts (e.g., financial reports, earnings announcements, and news releases) and macro-economic information. Private information consists of the proprietary information that individual analysts generate through data collection and analysis. In general, public information is less costly than private information. As risk pooling decreases earnings volatility and increases earnings predictability, the quality and usefulness of a firm's public information increases. Thus, financial analysts may rely more on public information (Barron et al. 1998; Mohanram and Sunder 2006). Accordingly, we propose hypothesis 1B.

Hypothesis 1B: Risk pooling increases analysts' reliance on public information in making forecasts.

The literature is unclear about the relationship between the precision of public and private information. Verrecchia (1982), Diamond (1985), and Kim and Verrecchia (1991) predict a negative relationship between the precision of these types of information. However, Kim and Verrecchia (1994, 1997) and Lundholm (1991) show a positive relationship between the precision of analysts' private and public information. This relationship is attributable to investors/analysts' limited capacity for information processing (Sims 2005). Because of the competing arguments on the relationship between the precision of the public and private information available to financial analysts, the effect of risk pooling on analysts' reliance on private information becomes an empirical question. We, therefore, propose Hypothesis 1C in null form.

Hypothesis 1C: Risk pooling does not affect analysts' reliance on private information in making forecasts.

2.4. Supply Chain Hierachy

2.4.1. Demand Variability in Supply Chain

To what extent demand variability can be reduced by risk pooling depends on the type of variability and the hierarchical position of a firm within a supply chain network. Osadchiy et al. (2015) study the source of sales variability in the supply chain and divide the demand variability into two components: a systematic risk component that occurs due to economic factors and an idiosyncratic component. They define systematic risk in demand as the correlation coefficient of change in sales with the market return, which is measured by the value-weighted market index for U.S. stock markets.

$$\rho_{Sales,Market} = \frac{Cov(Sales, Market)}{\sigma_{Sales} \times \sigma_{Market}}$$

Osadchiy et al. (2015) suggest that as a firm moves upstream in the supply chain network, that is, from a retailer to a wholesaler to a manufacturer, the systematic risk increases because firms of the same supply chain are from related industries and their co-movements with the market may be in the same direction. Hence, risk pooling reduces idiosyncratic risk, but not systematic risk. The increased systematic risk can increase the usefulness of financial analysts' knowledge of the overall market and the industries in which they specialize. Analysts are able to forecast more accurately when they have better knowledge of the industry and macro-economy (Clement 1999; Jacob et al. 1999). Accordingly, we propose Hypothesis 2A.

Hypothesis 2A: The effect of risk pooling on analyst forecast accuracy becomes more pronounced as firms move upstream along a supply chain network (e.g., from retailers to wholesalers to manufacturers).

As a firm moves up the supply chain, its performance is more related to that of the market, i.e., its systematic risk increases, assuming the same level of risk pooling. Accordingly, industry-level public information becomes more useful to financial analysts in making forecasts. Analysts are thus more likely to use public information for upstream firms than for downstream firms. If the relationship between the precision of public and private information is negative, analysts may be less likely to rely on the private information for upstream firms than for downstream firms. Accordingly, we propose Hypotheses 2B.

Hypothesis 2B: The effect of risk pooling on analysts' use of public information is stronger as firms move upstream along a supply chain network (e.g., from retailers to wholesalers to manufacturers).

As discussed above, the relationship between the precision of public and private information is unclear. Therefore, as firms move from downstream to upstream of the supply chain, whether the increased systematic risk strengthens or weakens the relationship between risk pooling and analysts' use of private information is an empirical question. We, therefore, propose Hypothesis 2C in null form.

Hypothesis 2C: The effect of risk pooling on analysts' use of private information does not change as firms move upstream along a supply chain network (e.g., from retailers to wholesalers to manufacturers).

3. Research Methodology

3.1. Data

Our sample consists of supplier-customer firm pairs from the period 2004 to 2010. According to SFAS Nos. 14 and 131, firms must disclose any customer sales comprising more than 10% of their sales revenues. We retrieve the names of customers for each firm in the COMPUSTAT industry segment customer file, and follow Fee and Thomas (2004) in identifying the customer's unique ID in the file by firm name.

To construct our supply chain network, we refer to social network analysis and focus on two types of node-level metrics—degree and centrality—to operationalize supply chain hierarchy. Kim et al. (2011) indicate that the concepts of social network analysis are particularly suitable for studying how the patterns of inter-firm relationships in a supply network translate into competitive advantages. We consider each firm to be a node in a supply chain network. In this directional network, A→B indicates that firm A is a supplier of firm B.

We retrieve financial statement data from COMPUSTAT, stock trading information from the CRSP monthly database, and analysts' earnings forecasts and actual earnings data from the I/B/E/S Detail History database. Forecasts issued by anonymous analysts are eliminated. Following previous studies, we retain the latest forecast issued by an analyst in a particular year (e.g., Clement 1999; Clement and Tse 2005). In addition, we include only those forecasts issued no earlier than one year ahead and no later than thirty days before the fiscal year-end. We exclude all analyst forecasts with no prior year data on forecast accuracy. To facilitate comparisons across firms, we deflate forecast errors by the firm's security price. Following Clement and Tse (2005), we exclude observations in which the price-deflated analyst forecast error is above 0.40 or below -0.40 and those with only one financial analyst.

3.2. Risk Pooling, the Supply Chain Hierarchy, and Model Specifications

In a social network analysis, the relationships and flows among connected nodes (Haythornthwaite 1996) are mapped and measured. In our context, each firm is a node in a large supply chain network that arises from the supplier-customer relationship. The information content of a specific node/firm depends on its position within the network. Figure 1 depicts the centrality/position of each firm within the supply chain network. The degree of centrality (*degree*) is defined as the number of unique nodes directly linked to a focal firm; the network links are not weighted (Shaw 1954). A higher value of *degree* indicates that the firm has access to more resources. As our network is directional, we estimate both the *Indegree* and *Outdegree* of each node within it, where *Indegree* measures the number of incoming links a firm has (in our case, the number of suppliers), while *Outdegree* measures the number of outgoing links (i.e., the number of customers). We use *Indegree* and *Outdegree* to construct our main proxies for a firm's position in the supply chain. Figure 1 depicts the five connected nodes/firms A, B, C, D, and E. For example, Node C is directly linked to B and D, its customer and supplier respectively, and has an *Indegree* of one and an *Outdegree* of one.

[Insert Figure 1 here]

3.2.1. Measure of Risk Pooling

Outdegree is our main proxy for risk pooling. We use two more risk pooling proxies to account for customer size. First is the number of large customers that a firm has (*Outdegree_Main*), where a large customer is one who contributes over 10% of the firm's sales.[3] Second is the percentage of large customers relative to all disclosed customers (*Per_Large*).

3.2.2. Measure of a Firm's Position in a Supply Chain Network

We propose a network hierarchical reduction algorithm based on *Indegree* centrality to measure the supply chain hierarchy (*Hdegree*). The minimum value of *Hdegree* represents manufacturing firms that have no suppliers, and the maximum value represents retailers that have no customers (i.e., they sell directly to individual consumers). Thus, the larger the *Hdegree*, the closer the firm is to its individual customers, and the further downstream it is in the supply chain.

The steps for estimating *Hdegree* are summarized as follows.

[3] SFAS No. 131 requires firms to disclose only the existence of and sales to individual external customers representing more than 10% of total firm revenues. However, we observe that in practice firms voluntarily release those customers who account for less than 10% of the total revenue.

1. Estimate the *Indegree* for each node (firm). Assign nodes where *Indegree* = 0 to the *Hdegree* = 1 group;
2. Remove any node where *Hdegree* = 1 from the supply chain network and re-estimate the *Indegree* for each node (firm) based on the reduced supply chain network. Assign the nodes whose *Indegree* = 0 to the *Hdegree* = 2 group;
3. Repeat step 2 to classify each node into the *Hdegree* = 3, 4, 5….. groups until every node has been assigned to a different *Hdegree* group.

Node A in Figure 1 has an *Hdegree* of 5 and node C has an *Hdegree* of 3.[4]

3.3. Model Specification

3.3.1. Effect of Risk Pooling on Forecast Accuracy

To analyze the effect of risk pooling and the supply chain hierarchy on analyst forecast accuracy, we estimate the following equation (1). Appendix A reports the definitions of the variables.

$$Abs\_FError_{it} = \beta_0 + \beta_1 Outdegree_{it} + \beta_2 Outdegree_{it} \times Hdegree_{it} + \beta_3 Hdegree_{it} + \beta_4 Size_{it} + \beta_5 Std\_ROE_{it} + \beta_6 ROA_{it} + \beta_7 Std\_Return_{it} + \beta_8 R\&D_{it} + Year\ and\ Industry\ Dummies + \varepsilon_{it} \quad (1)$$

Abs_FError_{it} is the absolute value of the mean forecast errors of all analysts following firm *i* in year *t* times 100, where mean forecast error is the actual earnings minus the mean forecast per share, deflated by the stock price at time *t* - 1. We use an analyst's latest one-year ahead annual forecast of earnings to estimate analyst forecast error. The smaller the *Abs_FError*, the higher the forecast accuracy. *Size* is the firm size, defined as the log value of total assets at the beginning of year *t*. We include firm size as a control variable because larger firms likely have more brokerage or investment banking business with analysts' brokerage houses (Bhushan 1989). Firm size is also a proxy of the quality of public information. Both factors affect analyst forecasting behavior. *Std_ROE* is the standard deviation of the return on equity in the preceding

[4] We also estimate the *Hdegree* based on *Betweenness* as a robustness check. *Betweenness* measures the number of times a node/firm occurs on the shortest path between any two other nodes/firms (Freeman 1977). It measures the potential control over other firms in the network, as any node that falls "between" other nodes will moderate the flow of resources between those nodes. The betweenness of each vertex is calculated, and those with a score of zero are classified into the *Hdegree* = i (i = 1) group and, then, deleted. The procedure is then repeated on the reduced graph, and the new vertex is classified into the *Hdegree* = i + 1 group and, then, those nodes with a score of i + 1 are deleted. We repeat the same procedure until all vertices have been deleted. As both measures give us very similar results, we present our results based on simple hierarchical reduction (*Outdegree* and *Indegree*) instead of the betweenness reduction.

four quarters. *ROA* represents return on assets. *Std_Return* is the standard deviation of the daily stock return over the past 12 months. *R&D* represents a firm's R&D investment intensity, measured as R&D expenses deflated by total assets at the beginning of year *t*. We include research and development expenses (*R&D*) as a proxy for the level of information asymmetry because analysts have relatively stronger incentives to follow firms with higher levels of information asymmetry (Aboody and Lev 2000, Barth et al. 2001). We include year and industry fixed-effects at the two-digit SIC level to control for the potential influence of year or industry on analyst forecast accuracy. To control for firm-effect, we assess statistical significance using standard errors clustering by firm.

A negative β_1 means that risk pooling increases the forecast accuracy, i.e., decreases forecast errors, whereas a positive β_2 suggests that as firms move down the supply chain, the effect of risk pooling in improving analyst forecast accuracy decreases.

3.3.2. Effect of Risk Pooling on the Use of Public and Private Information

To investigate the effect of risk pooling on analysts' use of public/private information for their forecasts, we use the models of Barron et al. (1998) to investigate the information environment faced by analysts. Barron et al. (1998) believe that analysts mainly use two types of information to make forecast decisions: common public information that is potentially available to all analysts (e.g., financial reports, corporate news, media articles, and macro-economic information) and idiosyncratic private information, which is specific to an individual analyst (e.g., generated through personal efforts in data collection and analysis).

The models of Barron et al. (1998) (Eq. 2 and Eq. 3) introduce the measures of the precision of common information (*H*, public information) and idiosyncratic information (*S*, private information). The precision of public information *H* represents the extent to which analysts depend on public or common information to make their forecasts, while the precision of private information *S* represents the extent to which analysts depend on private or idiosyncratic information to make their forecasts (Mohanram and Sunder 2006). Specifically, *SE* is the squared error of the consensus mean forecast, $(EPS_{actual} - EPS_{consensus})^2$; *D* is the dispersion among the forecasts ($STDEV^2$); *STDEV* is the standard deviation of the forecasts; and *N* is the number of analysts making forecasts for a firm. By incorporating both forecast accuracy and forecast dispersion, the model of Barron et al. (1998) provides an estimate of the precision of both public and private information.

An underlying assumption of Barron et al. (1998) and Mohanram and Sunder (2006) is that as the quality of the public information increases, financial analysts are more likely to use public information to make earnings forecasts. Hence, for the same squared error of consensus forecast (*SE*), the forecast dispersion (*D*) will be smaller. We thus observe an increase in *H*.[5]

$$H = \frac{SE - D/N}{[\left(1 - \frac{1}{N}\right)D + SE]^2} \tag{2}$$

$$S = \frac{D}{[\left(1 - \frac{1}{N}\right)D + SE]^2} \tag{3}$$

We build on Mohanram and Sunder's (2006) model and link supply chain hierarchical structure and risk pooling to public and private information (Eq. 4 and Eq. 5, respectively). Firms reporting losses or missing the market's expectations tend to disclose more information to avoid potential litigation, thereby influencing the information environment of analysts. Hence, we include the variables *Loss* (equal to 1 if a firm reports a loss in year *t* and 0 otherwise) and *Miss* (equal to 1 if a firm fails to meet the consensus forecast in year *t* and 0 otherwise). We include variables that are proven to influence a firm's information environment and hence analyst forecast accuracy. Inverse of stock prices, *IVPrice*, proxies for the brokerage commission rate (Brennan and Hughes 1991). *Coverage* measures the firm's information environment based on the 12-month average of the number of analysts who issue annual earnings forecasts captured in the I/B/E/S database for a specific firm. *Dispersion* measures the divergence of analyst forecasts and is estimated as the 12-month average of the standard deviation of analyst forecasts, deflated by the stock price at the beginning of the fiscal year. We control for the volatility of the stock, computed as the daily stock return standard deviation over the year because analysts are more likely to follow firms with higher levels

[5] Many researchers treat forecast dispersion as earnings uncertainty (e.g., Diether et al. 2002; Johnson 2004), while some interpret dispersion as a proxy for unpriced information risk arising when the underlying asset values are unobservable.

of return variability, as the expected trading benefits based on the acquisition of private information on these stocks are greater (Bhushan 1989).

$$H_{it}(Public\ informaiton) = \alpha_0 + \alpha_1 Outdegree_{it} + \alpha_2 Outdegree_{it} \times Hdegree_{it} + \alpha_3 Hdegree_{it} + \alpha_4 Size_{it} + \alpha_5 Std\_ROE_{it} + \alpha_6 ROA_{it} + \alpha_7 Std\_Return_{it} + \alpha_8 R\&D_{it} + \alpha_9 Loss_{it} + \alpha_{10} Miss_{it} + \alpha_{11} IVPrice_{it} + \alpha_{12} Coverage_{it} + \alpha_{13} Dispersion_{it} + Year\ and\ Industry\ Dummies + \varepsilon_{it} \quad (4)$$

$$S_{it}(Private\ information) = \beta_0 + \beta_1 Outdegree_{it} + \beta_2 Outdegree_{it} \times Hdegree_{it} + \beta_3 Hdegree + \beta_4 Size_{it} + \beta_5 Std\_ROE_{it} + \beta_6 ROA_{it} + \beta_7 Std\_Return_{it} + \beta_8 R\&D_{it} + \beta_9 Loss_{it} + \beta_{10} Miss_{it} + \beta_{11} IVPrice_{it} + \beta_{12} Coverage_{it} + \beta_{13} Dispersion_{it} + Year\ and\ Industry\ Dummies + \varepsilon_{it} \quad (5)$$

A positive α_1 (negative β_1) means that risk pooling enables analysts to depend more (less) on public (private) information to make forecasts. A negative α_2 (positive β_2) indicates that given the same level of risk pooling as firms move down the supply chain, analysts rely less (more) on public (private) information to make their forecasts.

4. Empirical Results and Discussion

4.1. Descriptive Statistics and Correlation Analysis

Table 1 reports the number of analysts and firms in different years. In total, we have 3,822 firm-years. Table 2 presents the descriptive statistics of the variables used in this study. We note that, on average, a firm is covered by around 10 analysts, the average *ROA* is -0.05, and 30% of the sample report losses. Table 3 presents the Pearson correlations among all the variables. Surprisingly, the correlations between the main risk pooling variable (*Outdegree*) and *Abs_Ferror*, *H*, and *S* are all insignificant. To draw a more meaningful conclusion, we estimate the relationships through multi-variate regression models to control for various factors associated with analysts' forecast error and their use of public vs. private information in sections 4.3 to 4.5. The correlation between *Outdegree* and *Hdegree* is negative and significant (corr. = -0.02; p = 0.048). Furthermore, the average risk pooling for *Hdegree* = 1 is 2.07, which decreases to 1.79 for *Hdegree* = 4. These findings suggest that risk pooling is relatively stronger in the upstream than the downstream of the supply chain.[6]

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[6] Osadchiy et al. (2015) claim that as systematic risk increases when firms moving up supply chains, the usefulness of risk pooling will decline. However, the lower effectiveness of risk pooling in reducing systematic risk does not directly translate into less use of risk pooling for the following reasons. First, if a manager uses less risk

[Insert Tables 1, 2, and 3 around here]

4.2. Relationship between Risk Pooling and Persistence of Accounting Numbers

We first estimate the correlation between risk pooling and the persistence of information from various financial reports to shed light on how risk pooling can improve the quality of public information, specifically financial reports. We follow the literature and use persistence as a proxy for a firm's public information quality. We compute the variance of the following information components, and the higher the variance, the lower the persistence of a variable: sales (*Sale*); earnings per share from operations (*OPEPS*); net cash flow from operating activities (*OANCF*); and various earning per share measures, including *EPSFI* (Earnings Per Share Diluted - Including Extraordinary Items), *EPSFX* (Earnings Per Share Diluted - Excluding Extraordinary Items), *EPSPI* (Earnings Per Share Basic - Including Extraordinary Items), and *EPSPX* (Earnings Per Share Basic - Excluding Extraordinary Items). We emphasize earnings as the literature (e.g., McNichols 2002) suggests that earnings are of high quality if they are persistent.

Table 4 presents the correlation between *Outdegree* and the persistence of various information components. At the 1% level, one unit increase in risk pooling (i.e., adding one more customer) is associated with a significant decrease in the variance of (an increase in the persistence of) sales, income from operation, net cash flow from operation, and various earnings per share components. Table 4 suggests that risk pooling is positively associated with a firm's public information quality, but the result of such univariate analysis should be interpreted with caution.

[Insert Table 4 around here]

pooling according to the level that it increases systematic risk, he may need to distinguish between idiosyncratic risk and systematic risk, as the findings of Osadchiy et al. (2015) suggest that managers may not distinguish between these two risks. Second, firms in the upstream may combine both risk pooling and financial hedging to hedge against systematic risk. Finally, increased systematic risk provides more room for both analysts and managers to incorporate their knowledge of the industry and macro-economy into forecasting the firm's future performance and make more accurate forecasts. Therefore, managers in the upstream may not shy away from risk pooling that increases systematic risk.

4.3. Empirical Tests of H1A and H2A

Table 5 presents the regression estimates of the effect of risk pooling and the supply chain hierarchy on analyst forecast accuracy. Column 1 is the base line model excluding proxies of risk pooling and supply chain hierarchy. These estimates are consistent with previous literature. For example, firms with more profit (*ROA*) have smaller forecast errors (coeff. = -8.83 and *t*-stat. = -9.17), while firms with higher uncertainty (*Std_ROE*; *Std_Return*) have larger forecast errors (coeff. = 3.86 and *t*-stat. = 8.95; coeff. = 148.53 and *t*-stat. = 9.31 respectively).

Columns 2, 3, and 4 show the effects of risk pooling on analyst forecast accuracy. We use three proxies for risk pooling: the number of total customers disclosed (*Outdegree*), the number of large customers (*Outdegree_Main*), and the percentage of large customers (*Per_Large*). The results suggest that risk pooling is negatively associated with forecast error, i.e., positively associated with forecast accuracy (coeff. = -1.12 and *t*-stat. = -5.72 for *Outdegree*; coeff. = -1.22 and *t*-stat. = -3.58 for *Outdegree_Main*; and coeff. = -1.41 and *t*-stat. = -1.99 for *Per_Large*). These results support H1A that risk pooling improves analyst forecast accuracy. For the control variables, the magnitudes and the significance levels in Columns 2, 3, and 4 are all similar to those in Column 1, indicating that our documented effect is consistent with the literature.

The coefficients on the interaction between the three risk pooling proxies and *Hdegree* are all significantly positive (coeff. = 0.91 and *t*-stat. = 6.12 for *Outdegree*; coeff. = 1.08 and *t*-stat. = 4.52 for *Outdegree_Main*; coeff. = 2.10 and *t*-stat. = 4.46 for *Per_Large*), indicating that the effect of risk pooling on improving analyst forecast accuracy is moderated as firms move from upstream to downstream along the supply chain. Using *Outdegree* as an example, when a firm moves downstream by one layer, assuming *Outdegree* = 1, the mean analysts' forecasts error of earnings is increased by 0.91% of the beginning stock price. These results support H2A.

[Insert Table 5 around here]

As a robustness check, we use Patatoukas's (2012) measure of customer-base concentration (*CC*) as another proxy for risk pooling and repeat the analysis.[7] In Patatoukas's (2012) study, the customer-base concentration in year *t* is measured across the firm's *n* customers as follows:

$$\mathrm{CC}_{i,t} = \sum_{j=1}^{n} \left(\frac{Sales_{i,j,t}}{Sales_{i,t}} \right)^2$$

where $Sales_{i,j,t}$ represents firm *i*'s sales from customer *j* in year *t*, and $Sales_{i,t}$ represents firm *i*'s total sales in year *t*. In essence, this measure captures both the number of customers a firm has and the relative importance of each customer to the firm's revenue. We use *CC* as another risk pooling proxy and report the regression estimates in Column 5 of Table 5. The coefficients on both *CC* and its interaction with *Hdegree* have the same signs as those reported in Columns 2 to 4 and both are significant, suggesting that our findings are robust to different measures of risk pooling.

4.4. Empirical Tests of H1B, H2B, H1C, and H2C

Tables 6 and 7 present the regression estimates of the effects of risk pooling and the supply chain hierarchy on analysts' use of public and private information, respectively. In Table 6, the coefficients on all three risk pooling proxies are positive and significant at the 5% level (coeff. = 50.22 and *t*-stat. = 2.75 for *Outdegree*; coeff. = 69.71 and *t*-stat. = 2.22 for *Outdegree_Main*; and coeff. = 154.54 and *t*-stat. = 2.37 for *Per_Large*), suggesting that as the level of risk pooling increases, analysts are more likely to rely on common or public information in generating their forecasts. Hence H1B is supported. In Table 7, the coefficients on all of the risk pooling proxies are negative and significant at the 5% level (coeff. = -96.50 and *t*-stat. = -2.72 for *Outdegree*; coeff. = -156.99 and *t*-stat. = -2.57 for *Outdegree_Main*; and coeff. = -319.31 and *t*-stat. = -2.52 for *Per_Large*), suggesting that analysts are less likely to rely on idiosyncratic or private information in generating their forecasts as risk pooling increases the precision of public information.

[7] We thank one of our referees for this suggestion.

In addition, in Table 6 the interactions between *Outdegree* and *Hdegree* (coeff. = -27.87 and *t*-stat. = -2.01), *Outdegree_Main* and *Hdegree* (coeff. = -48.86 and *t*-stat. = -2.19), and *Per_Large* and *Hdegree* (coeff. = -103.23 and *t*-stat. = -2.36) are all significantly negative, indicating that risk pooling plays a more significant role in increasing analysts' reliance on public information for firms upstream than for those downstream. Taking *Outdegree* as an example and assuming that *H* equals its mean value of -89.73, if everything else is the same, the extent to which analysts rely on common or public information to make a forecast increases by 56% (50.22/89.73) with each unit of increase in risk pooling (i.e., adding one more customer). Holding other variables constant, when *Hdegree* increases by one unit (moving one layer downstream of the supply chain), adding one more customer, the extent to which analysts rely on common or public information in generating their forecasts increases by only 25% ((50.22 - 27.87)/89.73). This supports H2B that the effect of risk pooling on analysts' use of public information is stronger as firms move from retailers to wholesalers to manufacturers.

Finally, in Table 7 the interactions between *Outdegree* and *Hdegree* (coeff. = 48.68 and *t*-stat. = 1.80), *Outdegree_Main* and *Hdegree* (coeff. = 87.48 and *t*-stat. = 2.02), and *Per_Large* and *Hdegree* (coeff. = 197.33 and *t*-stat. = 2.32) are all significantly positive, indicating that risk pooling plays a more important role in reducing analysts' reliance on private information for upstream firms than for downstream firms. Taking *Outdegree* as an example and assuming *S* equals its mean value of 381.52, by adding one more customer, the extent to which analysts rely on private information to make a forecast decreases by 25% (-96.50/ 381.52). When *Hdegree* increases by one unit (moving one layer downstream of the supply chain), adding one more customer, the extent to which analysts rely on private information to make a forecast decreases by only 12.5% ((-96.50 + 48.68)/381.52). This suggests that for the same unit change in risk pooling, analysts become less likely to depend on private information to make forecasts when firms move up the supply chain. At the mean level of precision of the public and private information, risk pooling increases analysts' reliance on public information to a greater degree than it reduces their reliance on private information, probably because analysts use private information to be competitive among peers. Risk pooling and a firm's position in the supply chain network do significantly affect analysts' reliance on public vs. private information, but do not significantly improve the explanatory power of the models, as the adjusted R^2 increases only marginally. The low adjusted R^2, though consistent with the literature, (round to 5% in Table 6 and 7% in Table 7) indicates that our understanding of the determinants of analysts' use of public vs. private information is still very limited.

[Insert Tables 6 and 7 around here]

4.5. Earnings Predictability and Analyst Forecast Accuracy

Studies suggest that earnings predictability is negatively related to forecast accuracy. In Section 4.2, we show that risk pooling is negatively related to variances of sales, cash, and earnings variables. Earnings predictability is positively associated with earnings volatility. Hence, we expect that risk pooling increases forecast accuracy through improving earnings predictability. In this section, we explore this mechanism. We take a two-stage approach. In stage one, we predict the volatility of ROA or the volatility of sales[8] using risk pooling and other control variables. In stage two, we include the residuals from stage one (*ROA_resid* and *Sale_resid*) in Equation (1). Table 8 reports the results. *ROA_resid* is positive and significant, suggesting that the component of earnings volatility unexplained by risk pooling has a significant positive (negative) impact on forecast error (accuracy). *Sale_resid* is negative but insignificant, probably because earnings are not only determined by sales but also by expenses. The coefficient on *Outdegree* remains negative and significant (coeff. = -1.22 and t-stat. = -4.77) and the coefficient on *Outdegree*×*Hdegree* remains positive and significant (coeff. = 0.98 and t-stat. = 4.80). This suggests that risk pooling reduces earnings (sales) volatility and increases forecast accuracy beyond the earnings (sales) volatility determined by other factors.

[Insert Tables 8 around here]

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[8] The volatility of sales is an important component of earnings and a consideration for forecasting, so is worthy of examination.

4.6. A Robustness Check

Guan et al. (2015) show that analysts are likely to follow a supplier-customer firm pair if the pair has strong economic ties. They also find that analysts who follow both a supplier and its customers provide more accurate earnings forecasts for the supplier firm than analysts who do not follow a firm's customers. Generally, firms that engage in more risk pooling have more customers, so analysts are more likely to follow the customers of these firms than those of firms that use less risk pooling. Our finding of a positive relationship between risk pooling and analyst forecast accuracy may be driven by analysts following both a supplier and its customer. To rule out this alternative explanation, for each firm-analyst-year observation we remove those with analysts following both the supplier and its customer and repeat our main analysis. Untabulated regression estimates based on a reduced subsample corresponding to Tables 5, 6, and 7 achieve very similar results, suggesting that our findings are not driven by analysts who follow both a supplier and its customer.

The literature shows that analyst forecast errors are serially correlated because analysts systematically underreact to earnings information (Abarbanell and Bernard 1992). To control for such a bias, we include analyst forecast errors from the previous period in Equations (1), (2), and (3), and repeat our analysis. The results remain robust with this new model specification.

Furthermore, to measure risk pooling, we require that for each supplier-customer pair both firms must be publicly listed and included in the COMPUSTAT database. As a robustness check, we test the models with a new risk pooling proxy based on the original supply chain data in which all types of customers are included: U.S. or foreign governments, various markets, and public or private firms. We repeat our analysis and the results are still robust with this new measure.

5. Conclusion

In this study, using a social network analysis method to operationalize risk pooling and supply chain hierarchy, we examine whether risk pooling reduces demand volatility and increases earnings predictability, thus improving analyst forecast accuracy. Risk pooling improves the precision of public information, so analysts are more likely to use public information in making their forecasts. The relationship between the precision of public and private information is unclear, so whether risk pooling increases or decreases analysts' reliance on private information is an empirical question. We further examine how a firm's position in the supply chain network affects the relationship between risk pooling and analyst forecasts accuracy, and between risk pooling and analysts' use of public (private) information. As the systematic risk component of demand volatility grows faster than the total demand volatility (Osadchiy et al. 2015), the increased systematic risk component increases the usefulness of analysts' industry and market-wide knowledge and, therefore, their understanding of a firm's public information. For any given level of risk pooling, the positive (negative) relationships between risk pooling and analyst forecast accuracy and between risk pooling and analysts' reliance on public (private) information is more pronounced in the upstream of the supply chain than in the downstream.

Our findings imply that a firm's customer base (risk pooling) and its position within the supply chain network not only affect the information environment of the firm, but also its information users, such as financial analysts. Specifically, a firm's risk pooling and position in the supply chain will influence how analysts use its financial information and their forecast accuracy. Serving as professional information intermediaries, sell-side financial analysts' earnings forecasts significantly affect investors' decision-making.

This study has some limitations. First, risk pooling might affect analyst forecast accuracy through other channels. For example, risk pooling may affect firms' earnings quality and frequency of voluntary disclosure. Previous studies show that firms manage earnings, report more conservatively, and provide less voluntary disclosures if they depend on a few large customers (Raman and Shahrur 2008; Hui et al. 2012; Crawford et al. 2016), and such disclosure affects analyst forecast accuracy (Salerno 2014; Mensah et al. 2004; Hassell et al. 1988).

Second, we investigate only the number of customers as a proxy for risk pooling. In fact, firms can adopt risk pooling in multiple ways (e.g., number of warehouse locations, number of geographic operations). Future research can compare the effectiveness of different types of risk pooling in terms of helping analysts make forecasts.

Third, we study the effect of risk pooling on only one type of accounting information user, financial analysts. Similar effect can be applicable to equity investors and creditors. As the quality of firm-specific information increases, equity investors are more likely to acquire and use firm-specific information to make investment decisions. An increase in the proportion of firm-specific information impounded in stock prices is likely to result in lower stock return synchronicity (Durnev et al. 2003). For creditors, the link between firm-specific information quality and credit spreads, as modeled by Duffie and Lando (2001) implies that as the accounting quality increases, debt investors are less likely to demand higher returns. Future research can link risk pooling to stock synchronicity and credit spreads to reveal further insights into the effect of risk pooling on a firm's information environment.

Lastly, firms with more foreign customers may have higher forecast errors. Our proxy of risk pooling does not differentiate between domestic and foreign customers because of data availability.[9] Future research could make this distinction when calculating risk pooling to gain further insights into how different types of risk pooling affect analyst forecast accuracy.

[9] We thank one of our referees for raising this point.

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Figure 1 Centrality Measurement with Five Nodes and Four Edges

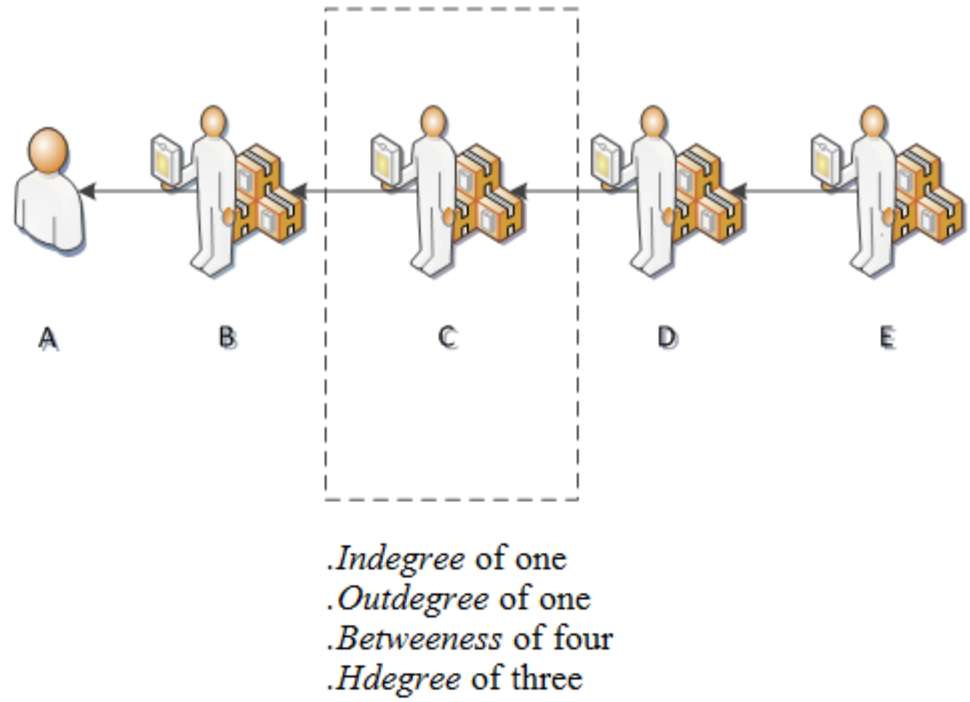

Table 1 Number of Firms over Time

Year	N. of Distinct Firms
2004	579
2005	593
2006	579
2007	607
2008	571
2009	364
2010	529
Total	3,822

Table 2 Summary Statistics

Variable	Mean	Median	Std. Dev.	Min	Max
Abs_FError	0.04	0.85	0.1	0	0.83
H (Public Information)	-89.73	5.00	926.72	-8,000	829.91
S (Private Information)	381.52	16.55	1,819.84	0	15,193.7
Hdegree	4.37	1.00	3.49	1	10
Outdegree	2.08	2.00	1.84	1	24
Outdegree_Main	1.24	1.00	0.94	1	5
Per_Large	0.71	1.00	0.41	1	1
Size	6.47	6.24	1.67	3.13	11.15
Std_ROE	0.12	0.02	0.41	0	2.88
ROA	-0.05	0.03	0.22	-0.91	0.26
Std_Return	0.03	0.03	0.02	0.01	0.09
R&D	0.12	0.08	0.14	0	0.74
Loss	0.3	0.00	0.46	0	1
Miss	0.5	1.00	0.5	0	1
IVPrice	0.14	0.07	0.19	0.01	1.1
Coverage	9.55	7.00	7.75	1	38
Dispersion	0.03	0.01	0.08	0	0.54

Table 3 Pearson Correlation

	Abs_FError	***H***	***S***	***Hdegree***	***Outdegree***	***Outdegree_ Main***	***Per_Large***	***Coverage***
H	0.03**							
S	-0.07***	-0.92***						
Hdegree	-0.03*	0.05***	-0.05***					
OutDegree	-0.02	0.01	-0.03	-0.02**				
Outdegree_Main	0.01	0.00	-0.02	0.03	0.23***			
Per_Large	0.04	0.01	-0.02	0.06	-0.30***	0.60***		
Coverage	-0.16***	0.13***	-0.14***	0.49***	-0.04***	-0.04***	-0.04***	
Dispersion	0.78***	0.01	-0.05***	-0.04**	0.00	0.00	0.00	-0.16***

Note: This table presents Pearson correlations among main variables used in the empirical analyses. *Hdegree* measures the hierarchical position of a firm within a supply chain network. A lower value of *Hdegree* indicates that a firm is closer to the upstream of a supply chain; while *Outdegree*, *Outdegree_Main*, and *Per_Large* represent the number of customers, number of large customers, and percentage of large customers, respectively. The superscripts ***, **, and * denote the 1%, 5%, and 10% levels of significance using two-tail tests, respectively.

Table 4 Relationship between Risk Pooling and Persistence of Accounting Numbers

	Outdegree	***Sales***	***OANCF***	***EPSFI***	***EPSFX***	***EPSPI***	***EPSPX***
Sales	-0.14***						
OANCF	-0.15***	0.65***					
EPSFI	-0.05***	0.08***	0.08***				
EPSFX	-0.05***	0.08***	0.08***	0.95***			
EPSPI	-0.05***	0.08***	0.08***	0.99***	0.94***		
EPSPX	-0.05***	0.08***	0.08***	0.95***	0.99***	0.95***	
OPEPS	-0.05***	0.11***	0.12***	0.79***	0.82***	0.78***	0.82***

Note: This table presents Pearson correlations among the number of customers (risk pooling) and the variances of demand, cash flow from operations, and various earnings measures. Definitions of variables are presented in Appendix A. The superscripts ***, **, and * denote the 1%, 5%, and 10% levels of significance using two-tail tests, respectively.

Table 5 The Relationship among Risk Pooling, Supply Chain Hierarchy, and Forecast Accuracy

	Dependent variable = *Abs_FError*				
	(1)	(2)	(3)	(4)	(5)
Outdegree		-1.12			
		(-5.72)***			
Outdegree×Hdegree		0.91			
		(6.12)***			
Outdegree_Main			-1.22		
			(-3.58)***		
Outdegree_Main×Hdegree			1.08		
			(4.52)***		
Per_Large				-1.41	
				(-1.99)**	
Per_Large×Hdegree				2.10	
				(4.46)***	
CC					-2.58
					(-2.24)**
CC×Hdegree					2.52
					(2.58)***
Hdegree		0.01	-0.01	-0.02	0.06
		(0.19)	(-0.25)	(-0.33)	(3.17)***
Size	-0.74	-1.02	-0.97	-1.00	-0.36
	(-6.10)***	(-7.83)***	(-7.31)***	(-7.46)***	(-7.41)***
Std_ROE	3.86	3.86	3.85	3.82	1.45
	(8.95)***	(8.98)***	(8.94)***	(8.88)***	(7.85)***
ROA	-8.83	-8.73	-8.75	-8.73	-4.47
	(-9.17)***	(-9.11)***	(-9.10)***	(-9.10)***	(-11.51)***
Std_Return	148.53	144.03	145.92	146.20	68.63
	(9.31)***	(9.05)***	(9.16)***	(9.19)***	(10.98)***
R&D	-6.28	-6.41	-6.28	-6.40	-2.90
	(-4.14)***	(-4.25)***	(-4.16)***	(-4.23)***	(-4.70)***
Constant	3.53	5.60	5.09	4.70	1.94
	(2.22)**	(3.75)***	(3.11)***	(2.83)***	(3.05)***
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	3,822	3,822	3,822	3,822	3,822
R-squared	0.18	0.20	0.20	0.20	0.19

Note: This table shows the regression results of estimating Equation (1), which examines the relationship among risk pooling, supply chain hierarchy, and forecast errors, based on the full model. Definitions of variables are presented in Appendix A. *Abs_FError* is the absolute value of the *FError*, which equals the actual earnings minus the mean forecast, deflated by the stock price at the beginning of the fiscal year. *Hdegree* measures the hierarchical position of a firm within a supply chain network. A lower value of *Hdegree* indicates that a firm is closer to the upstream of a supply chain; while *Outdegree*, *Outdegree_Main*, and *Per_Large* represent the number of customers, number of large customers, and percentage of large customers, respectively. The superscripts ***, **, and * denote the 1%, 5%, and 10% levels of significance using two-tail tests, respectively.

Table 6 The Relationship among Risk Pooling, Supply Chain Hierarchy, and Reliance on Public Information

	Dependent variable = *H* (Public information)			
	(1)	(2)	(3)	(4)
Outdegree		50.22		
		(2.75)**		
Outdegree×Hdegree		-27.87		
		(-2.01)**		
Outdegree_Main			69.71	
			(2.22)**	
Outdegree_Main×Hdegree			-48.86	
			(-2.19)**	
Per_Large				154.54
				(2.37)**
Per_Large×Hdegree				-103.23
				(-2.36)**
Hdegree		-8.87	-5.37	-2.39
		(-1.72)*	(-1.08)	(-0.52)
Size	70.73	77.90	80.59	81.59
	(4.16)***	(4.51)***	(4.62)***	(4.67)***
Std_ROE	45.50	46.87	45.88	46.49
	(1.14)	(1.17)	(1.15)	(1.16)
ROA	-142.63	-141.24	-143.29	-140.04
	(-1.36)	(-1.34)	(-1.36)	(-1.33)
Std_Return	-1012.88	-1,195.96	-1,055.65	-1,009.79
	(-0.66)	(-0.78)	(-0.69)	(-0.66)
R&D	64.55	61.03	52.70	53.59
	(0.45)	(0.43)	(0.37)	(0.38)
Loss	118.09	122.63	120.88	122.11
	(2.49)***	(2.59)**	(2.55)**	(2.58)***
Miss	101.08	100.01	99.53	99.24
	(3.15)***	(3.12)***	(3.11)***	(3.10)***
IVPrice	-547.20	-510.96	-510.44	-508.52
	(-4.78)***	(-4.44)***	(-4.43)***	(-4.41)***
Coverage	3.71	5.28	4.92	4.90
	(1.26)	(1.77)*	(1.64)	(1.63)
Dispersion	996.51	1,004.15	998.39	987.64
	(4.18)***	(4.22)***	(4.19)***	(4.15)***
Constant	-849.38	-909.72	-915.06	-942.92
	(-5.21)***	(-5.50)***	(-5.49)***	(-5.58)***
Year fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Observations	3,822	3,822	3,822	3,822
R-squared	0.05	0.05	0.05	0.05

Note: This table shows the regression results of estimating Equation (4), which examines the relationship among risk pooling, supply chain hierarchy, and the precision of public information, based on the full model. Definitions of variables are presented in Appendix A. *H* is the precision of public information, following the definition of Barron et al. (1998). We use this as a proxy for analysts' reliance on public information. *Hdegree* measures the hierarchical position of a firm within a supply chain network. A lower value of *Hdegree* indicates that a firm is closer to the upstream of a supply chain; while *Outdegree*, *Outdegree_Main*, and *Per_Large* represent the number of customers, number of large customers, and percentage of large customers, respectively. The superscripts ***, **, and * denote the 1%, 5%, and 10% levels of significance using two-tail tests, respectively.

Table 7 The Relationship among Risk Pooling, Supply Chain Hierarchy, and Reliance on Private Information

	Dependent variable = *S* (Private information)			
	(1)	(2)	(3)	(4)
Outdegree		-96.50		
		(-2.72)**		
Outdegree×Hdegree		48.68		
		(1.80)*		
Outdegree_Main			-156.99	
			(-2.57)***	
Outdegree_Main×Hdegree			87.48	
			(2.02)**	
Per_Large				-319.31
				(-2.52)**
Per_Large×Hdegree				197.33
				(2.32)**
Hdegree		11.69	7.13	-2.51
		(1.17)	(0.74)	(-0.28)
Size	*-141.3*	-152.49	-160.46	-160.81
	*(-4.50)****	(-4.54)***	(-4.73)***	(-4.73)***
Std_ROE	*-90.73*	-91.89	-89.33	-90.20
	(-1.17)	(-1.18)	(-1.15)	(-1.16)
ROA	*268.13*	268.88	276.73	264.78
	(1.31)	(1.32)	(1.35)	(1.30)
Std_Return	*-2287.1*	-1,913.58	-2,250.46	-2,354.81
	(-0.77)	(-0.64)	(-0.75)	(-0.79)
R&D	*-368.16*	-363.73	-343.07	-348.00
	(-1.33)	(-1.31)	(-1.24)	(-1.25)
Loss	*-359.5*	-367.93	-365.26	-366.81
	(-.3.91)***	(-4.00)***	(-3.97)***	(-3.99)***
Miss	*-159.49*	-159.43	-158.48	-156.70
	(-2.56)***	(-2.56)**	(-2.54)**	(-2.52)**
IVPrice	*1597.27*	1,542.51	1,542.15	1,536.32
	(7.18)***	(6.89)***	(6.88)***	(6.85)***
Coverage	*-11.97*	-14.47	-13.37	-13.62
	(-2.1)**	(-2.49)**	(-2.30)**	(-2.34)**
Dispersion	*-3047.1*	-3,065.12	-3,060.29	-3,033.35
	(-6.58)***	(-6.62)***	(-6.61)***	(-6.55)***
Constant	*2001*	2,127.55	2,163.18	2,210.46
	(6.32)***	(6.62)***	(6.68)***	(6.73)***
Year fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Observations	3,822	3,822	3,822	3,822
R-squared	0.07	0.07	0.07	0.079

Note: This table shows the regression results of estimating Equation (5), which examines the relationship among risk pooling, supply chain hierarchy, and the precision of private information, based on the full model. Definitions of variables are presented in Appendix A. *S* is the precision of private information, following the definition of Barron et al. (1998). We use this as a proxy for analysts' reliance on private information. *Hdegree* measures the hierarchical position of a firm within a supply chain network. A lower value of *Hdegree* indicates that a firm is closer to the upstream of a supply chain; while *Outdegree*, *Outdegree_Main*, and *Per_Large* represent the number of customers, number of large customers, and percentage of large customers, respectively. The superscripts ***, **, and * denote the 1%, 5%, and 10% levels of significance using two-tail tests, respectively.

Table 8 The Relationship among Risk Pooling, Supply Chain Hierarchy, and Forecast Accuracy: Two-stage Approach

	Dependent variable = *Abs_FError*		
	(1)	(2)	(3)
Outdegree	-1.22		
	(-4.77)***		
Outdegree×Hdegree	0.98		
	(4.80)***		
Outdegree_Main		-1.56	
		(-4.30)***	
Outdegree_Main ×Hdegree		1.32	
		(4.92)***	
Per_Large			-1.65
			(-2.27)**
Per_Large×Hdegree			2.31
			(4.65)***
ROA_resid	2.15	2.14	2.12
	(2.26)**	(2.26)**	(2.24)**
Sale_resid	-0.49	-0.48	-0.47
	(-1.49)	(-1.47)	(-1.46)
Size	-0.99	-0.99	-1.00
	(-7.26)***	(-7.31)***	(-7.30)***
Std_ROE	3.63	3.61	3.58
	(8.25)***	(8.19)***	(8.14)***
ROA	-9.24	-9.29	-9.32
	(-9.11)***	(-9.15)***	(-9.19)***
Std_Return	149.38	148.44	148.52
	(9.24)***	(9.19)***	(9.20)***
R&D	-5.71	-5.60	-5.69
	(-3.56)***	(-3.49)***	(-3.55)***
Constant	5.36	5.17	4.59
	(3.22)***	(3.12)***	(2.73)***
Year fixed effect	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes
Observations	3,822	3,822	3,822
R-squared	0.20	0.20	0.20

Note: This table examines how risk pooling reduces earnings volatility and, hence, increases forecast accuracy. We took a two-stage approach. In stage one, we predict the volatility of ROA or the volatility of sales using risk pooling variables and other control variables. In the second stage, we include the residuals from stage one (*ROA_resid* and *Sale_resid*) in Equation (1). Definitions of variables are presented in Appendix A. *Abs_FError* is the absolute value of the *FError*, which equals the actual earnings minus the mean forecast, deflated by the stock price at the beginning of the fiscal year. *Hdegree* measures the hierarchical position of a firm within a supply chain network. A lower value of *Hdegree* indicates that a firm is closer to the upstream of a supply chain; while *Outdegree*, *Outdegree_Main*, and *Per_Large* represent the number of customers, number of large customers, and percentage of large customers, respectively. The superscripts ***, **, and * denote the 1%, 5%, and 10% levels of significance using two-tail tests, respectively.

Appendix A Variable Definitions

Variable	Definition
FError	Actual earnings minus the mean of forecasts, deflated by the stock price at the beginning of the fiscal year times *100*
Abs_FError	Absolute value of the *FError*
H	The precision of common/public information, which also represents analysts' reliance on public information in making forecasts. Following Barron et al. (1998), $H = \frac{SE - D/N}{[\left(1-\frac{1}{N}\right)D + SE]^2}$ where *SE* is the squared error of the consensus mean forecast (measured as (*EPSactual* - *EPSconsensus*)^2); *D* is the dispersion among the forecasts (measured as *STDEV*^{2}, where *STDEV* is the standard deviation of estimates from I/B/E/S); and *N* is the number of analysts making forecasts.
S	The precision of idiosyncratic/private information, which also represents analysts' reliance on private information in making forecasts. Following Barron et al. (1998), $S = \frac{D}{[\left(1-\frac{1}{N}\right)D + SE]^2}$
Hdegree	The hierarchical position of a firm within a supply chain network. The smaller the *Hdegree*, the closer the firm operates to the raw material, and the further upstream the firm sits in the supply chain.
Outdegree	The number of customers a firm has
Outdegree_Main	The number of large customers a firm has, where a large customer is one whose purchases account for more than 10% of the firm's total sales
Per_Large	The percentage of all customers who are large customers as disclosed by the firm
Size	Log value of firm total assets at the beginning of the fiscal year
Std_ROE	The standard deviation of return on equity in the preceding four quarters
ROA	Return on assets, measured as earnings divided by total assets
Std_Return	The standard deviation of daily stock returns over the year
R&D	Research and development expense deflated by total assets at the beginning of the fiscal year
Loss	Equals 1 if earnings are negative, and 0 otherwise
Miss	Equals 1 if earnings per share is smaller than the analysts' forecast consensus, and 0 otherwise
IVPrice	Inverse value of the price at the previous fiscal year end
Coverage	The 12-month average of the number of analysts who issue annual earnings forecasts captured in the I/B/E/S database for a firm
Dispersion	The 12-month average of the standard deviations of analyst forecasts, deflated by the stock price at the beginning of the fiscal year
Sales	Variance of Sales
OANCF	Variance of Operating Activities Net Cash Flow
EPSFI	Variance of Earnings Per Share (Diluted) - Including Extraordinary Items
EPSPX	Variance of Earnings Per Share (Diluted) - Excluding Extraordinary Items
EPSPI	Variance of Earnings Per Share (Basic) - Including Extraordinary Items
EPSPX	Variance of Earnings Per Share (Basic) - Excluding Extraordinary Items
OPEPS	Variance of Earnings Per Share from Operations