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Supplier concentration and analyst forecast bias

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ABSTRACT

This study examines the relationship between analyst forecast dispersion or accuracy and supplier concentration of listed firms in China from 2008 to 2019. Our findings suggest that higher supplier concentration is associated with lower analyst forecast dispersion, which can be attributed to the increased attention from analysts. Moreover, this effect is more pronounced when firms have less bargaining power and higher institutional ownership, indicating a greater reliance on the supply chain. Our study highlights the importance of disclosing supply chain information, which provides insights beyond those of traditional financial information.

1. Introduction

In the past decade, academic research has paid increasing attention to the supply chain relationship of firms, recognizing the critical role of external stakeholders such as suppliers and customers in production and operations. Studies demonstrate that corporate performance can be affected by other partners in the supply chain (Hertzel et al., 2008; Pandit et al., 2011; Patatoukas, 2012). In addition, Dhaliwal et al. (2016) find that the financial status of customers can influence the asset structure of their suppliers. Furthermore, studies find that the geographic proximity of suppliers and customers positively affects suppliers' innovation (e.g., Chu et al., 2019), particularly when the firm has a higher purchasing ratio than its customers and a strong capability for critical innovation. In addition, research explores the effects of the supply chain on a range

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of topics, such as earnings management (Raman and Shahrur, 2008), asset structure (Banerjee et al., 2008), bank loans (Campello and Gao, 2017) and financing cost (Dhaliwal et al., 2016).

Studies mainly focus on the supply chain's impact on firms, while few explore the information contained within the chain. The supplier–customer relationship is a key contractual element between upstream and downstream firms, and it represents a type of non-financial information that can be captured and analyzed by external investors, especially analysts. Owing to the technological advances of the Internet, this information is increasingly accessible and processing costs are decreasing. Analysts are now paying increasing attention to non-financial data, such as environmental performance disclosure and political uncertainty, in addition to standard financial data and stock prices. A supply chain is a form of relational non-financial information that is distributed across multiple subjects. As Guan et al. (2015) and Luo and Nagarajan (2015) suggest, tracking the information disclosed by leading suppliers and customers can improve analyst accuracy and provide more accurate capital signals to the capital market.

In this study, we expand research in this field by exploring the value of information in the supply chain. We examine this issue from the perspective of analyst forecast behavior. Specifically, we investigate the influence of supplier concentration on analyst forecast dispersion, or error, and the role of information in the supply chain on the capital market. Current proxies for corporate information transparency may have limited reliability and validity, as they mainly reflect a firm's financial and stock price information, such as accrued earnings management (Bhattacharya et al., 2003) and accounting information quality (Kim and Verrecchia, 2001), without fully considering supply chain information. We determine whether supply chain information is beneficial to analyst forecasts, thus broadening understanding in this field.

We construct a panel dataset of Chinese listed firms from 2007 to 2019, containing information on supplier concentration and proxies for analyst forecast behavior. The China Securities Regulatory Commission's (CSRC) requirement that listed firms disclose their top five suppliers and purchasing ratios in 2007 enables us to establish this dataset. Compared with the developed markets of Europe and America, the Chinese market is a late starter and has a relatively poor information environment (Piotroski et al., 2015). Our study highlights the potential for information discovery in the supply chain, which could help refine and improve the Chinese market.

We estimate a panel regression in which analyst forecast dispersion is regressed on supplier concentration and other firm characteristics. We find that analyst forecast dispersion is negatively associated with supplier concentration. We test the hypothesis that supplier concentration could reduce financial information transparency, and obtain consistent results. Our analysis suggests that a firm with a higher supplier concentration has lower information transparency due to more severe agency problems. Low financial transparency has a negative impact on analyst forecasts, but the positive effect of centralized suppliers is more pronounced. In addition, we find that high financial transparency helps alleviate the negative relationship between supplier concentration and analyst forecast dispersion. Our findings indicate that supply chain information and traditional financial information are two different sources that impact analyst forecasts and that supplier concentration plays a significant role in promoting analyst forecasts for firms with high institutional shareholding ratios and strong industry competition. Furthermore, we address endogeneity problems (e.g., omitted variable bias and reverse causality problems) using an instrumental variable (IV) regression and propensity score matching (PSM). Our primary findings remain intact after conducting various robustness tests, including substituting our proxies for supplier concentration and analyst forecast behavior and changing the model specifications by adding control variables. Our results are robust and significant.

Our study contributes to three strands of literature. First, we explore the types of non-financial information that analysts can mine, a key research direction in recent years (Griffin et al., 2020; Yu et al., 2020). We demonstrate the value of supply chain information and its importance in disclosure, and provide empirical evidence of the association between supplier concentration and analyst forecast behavior.

Second, our study contributes to research on the impact of contractual relationships between upstream and downstream firms in the supply chain. Studies focus mainly on how the supply chain can affect the firm itself, such as the effects on corporate decision-making (Chu et al., 2019) and asset structure (Banerjee et al., 2008). However, the influence of the supply chain on external stakeholders (such as analysts) receives limited attention in the literature. Thus, in this study, we seek to expand the exploration of the information contained in the supply chain and provide a valuable supplement to this field.

Finally, our study adds to the body of literature on the factors that affect the spread and accuracy of analyst forecasts and firms' supply chain information. We find that analysts' increased tracking of supply chains can improve their forecasts of firm performance (Guan et al., 2015; Luo and Nagarajan, 2015). A centralized supply chain decreases the barriers to analyst tracking and thus, by attracting additional analysts to access information in the supply chain, it improves information efficiency. Our research provides new evidence for the inclusion of supply chain information in decision-making and forecasts. The results encourage the market to pay more attention to enterprise supply chain information and improve market efficiency.

The remainder of the study is structured as follows. In Section 2, we review the relevant literature and present our hypotheses. Section 3 outlines the data sources and empirical design. Section 4 evaluates the influence of supplier concentration, explores the financial information transparency effect and discusses the potential mechanism. In addition, we examine the heterogeneous effect of transparency, competitive concentration and the institutional shareholding ratio. In Section 5, we conduct a series of robustness checks. Section 6 further examines some of our findings. Finally, Section 7 concludes this study.

2. Literature review and hypothesis development

Analysts are the external stakeholders of a firm and their primary goal is to predict information accurately (Hong and Kubik, 2003). The more precise the information they possess, the more likely they are to make accurate predictions. However, Zhang (2006a) finds that professional investment intermediaries and sell-side analysts are prone to behavioral biases under high information uncertainty. The effect of an increasingly centralized supply chain on firms' information transparency remains a matter of debate. Academic evidence suggests that supplier/customer concentration can positively or negatively affect information transparency.

Firms tend to maintain long-term cooperative relationships with fixed suppliers, which can benefit their operations and cooperation. According to Dyer (1996), firms can gain higher value-added from the supply chain if they maintain longer supplier–customer relationships. Conversely, if the contractual relationship is broken, reconstructing a similar relationship will require cost inputs (Titman and Trueman, 1986). This gives firms an incentive to sustain their existing supply chains. To develop a long-term cooperative relationship and ensure its longevity, it is important to reduce information asymmetry (Costello, 2013), which requires information exchange between firms. Consequently, firms are likely to disclose some information to other firms in the supply chain to maintain cooperation.

Furthermore, Hui et al. (2012) and Cen et al. (2016) demonstrate that major customers have incentives to monitor their suppliers. Cen et al. (2016) prove that major customers tend to screen and monitor their suppliers to ensure the stability of the supply chain. Suppliers have the same incentive to promote information exchange and reduce information asymmetry in the supply chain.

Conversely, a firm with a high level of supplier concentration will rely on a few major suppliers. According to bargaining power theory (Nagarajan and Bassok, 2008), this could place the firm in an unfavorable position, as suppliers may have more power than the firm does. To meet the expectations of large suppliers, firms with market weaknesses may increase their core earnings through classified transfers, a type of earnings management activity (McVay, 2006; see also Barua et al., 2010). Baumol (1986) finds that relational transactions in the supply chain can promote specific investments between firms and suppliers or customers, which can negatively affect the quality of accounting information.

The cooperative relationship between suppliers and customers can promote supply chain integration, reducing the information asymmetry between the parties. Research shows that analysts tracking the supply chain can make better firm forecasts and improve their forecast accuracy than analysts who overlook or ignore supply chain information (Guan et al., 2015; Luo and Nagarajan, 2015). The structural information of the supply chain plays a critical role in analyst forecast behavior. First, the supply chain structure itself is an incremental and essential source of non-financial information, which augments analysts' analytical capabilities. The impact stems directly from analysts' acquisition of supply chain structure information pertaining to their focal firms. Second, by leveraging supply chain structure information and tracking other firms within the supply chain, analysts can improve their forecast accuracy and mitigate forecast dispersion. The effect is particularly pronounced when close business ties exist among the firms operating within the supply chain because their information is likely to be complementary (Guan et al., 2011). Sustaining the supply chain facilitates information exchange among firms and promotes long-term collaboration. Intensified business interdependencies often manifest as correlated financial information. For instance, a supplier's profitability may be related to the performance of its customer. Therefore, by scrutinizing the circumstances of closely connected firms in the supply chain, analysts can derive abundant and precise insights concerning firm performance and potential risks. Moreover, firms in the same supply chain are likely to be influenced by shared macroeconomic conditions or external shocks. Consequently, monitoring primary firms along the supply chain enables analysts to better capture these dynamics (Pandit et al., 2011).

In conclusion, we show that high supplier concentration, a sign of close business ties between suppliers and customers, may help analysts to obtain a greater volume of information with improved disclosure quality, thereby improving their forecast accuracy.

H1a: Firms with higher supplier concentration experience lower dispersion in analyst forecasts and more accurate results.

H1b: Firms with lower supplier concentration experience greater dispersion in analyst forecasts and less accurate results.

Research shows that a firm's performance can influence the performance of other firms in its supply chain. Olsen and Dietrich (1985) demonstrate that a firm's monthly sales announcements can affect its suppliers' stock prices. Hertzel et al. (2008) propose that when a firm files for bankruptcy, its suppliers experience negative stock returns. Shahrur et al. (2010) observe that changes in the returns of customer industries often precede those of supplier industries, suggesting that there is a sequence of information transmission between suppliers and customers. Moreover, Guan et al. (2015) suggest that the effect of information transfer in the supply chain is related to relationship strength, with a closer economic connection leading to stronger information transfer and greater complementarity.

When an industry is characterized by fierce competition, a firm's competitive advantages are low. This increases its exposure to supply chain risks, as suppliers can easily find alternative partners (Han et al., 2012). To counter this, firms must take proactive steps to strengthen their economic ties with their suppliers. Our prediction is that information externalities in the supply chain will be more substantial for firms in competitive industries, and that the association between analyst forecast behavior and supplier concentration will be more pronounced in this situation.

The increase in institutional ownership has profound implications for the availability of information to analysts. According to Yan and Zhang (2009), institutional investors can increase their knowledge before an announcement, thereby improving disclosure. Mitra and Cready (2005) find that a high institutional shareholding ratio can effectively reduce the use of accounting discretion and improve information effectiveness. We hypothesize that a high institutional ownership ratio will benefit analyst forecasts and enhance the strength of our findings.

H2: For firms with high institutional ownership and intense industry competition, the correlation between supplier concentration and analyst forecast behavior is stronger.

3. Data and methodology

3.1. Data and sample

We obtain data on accounting, suppliers and analyst forecast behavior from the China Stock Market & Accounting Research (CSMAR) database. In this study, all industry classifications follow the Guidelines for the Industry Classification of Listed Firms issued by the CSRC in 2012. Under this industry classification, every industry is represented by a capital letter. Considering the large number of firms in the manufacturing industry, the classification standard is further subdivided and represented by a capital letter and a number.

Since 2007, the CSRC has required listed firms to disclose their top five suppliers and the proportion of their total purchases from each. Our sample consists of all listed firms in China, with the exception of those in the finance and utility industries, for the 2008–2019 period, resulting in 9,912 firm-year observations from 1,965 unique firms. To mitigate the impact of outliers, we winsorize all continuous variables at the 1st and 99th percentiles.

3.2. Variable construction

3.2.1. Supplier concentration

Owing to a lack of detailed data on suppliers, many studies use the purchasing ratio of major suppliers to measure supplier concentration (Itkowitz, 2013; Dhaliwal et al., 2016). In comparison, customer data are much more readily available, such that the literature concerning the measurement of customer concentration is much richer. Following Dhaliwal et al. (2016) and Itkowitz (2013), we choose three methods to construct proxy variables for supplier concentration. As noted, the CSMAR database includes only the top five suppliers of each listed firm. Thus, when calculating supplier concentration, we use these five major suppliers to represent the entire supply chain for each firm. As a first measure, we adopt the Herfindahl–Hirschman index (HHI), which is a common approach in the literature, to capture customer concentration (Patatoukas, 2012; Campello and Gao, 2017). Specifically, the HHI is formulated as follows:

$$SupC5_{it} = \sum_{j=1}^{5} \left(\frac{Sales_{ijt}}{Sales_{it}} \right)^2,$$

where $Sales_{ijt}$ represents the amount purchased by firm i from supplier j in year t and $Sales_{it}$ represents firm i's total amount purchased in year t. This variable ranges from zero to one, with a higher value corresponding to a more concentrated supplier base. If the value is zero, the firm has no supplier disclosure, whereas a value of one means that the firm has only one major supplier.

For robustness, we construct two other measures of supplier concentration. For our second measure, we construct $SupC3$ using data on the top three major suppliers. Then, our third method uses the sum of the purchasing ratio of the top five suppliers to proxy supplier concentration, which is a classical method frequently used in the literature (Pearson and Trompeter, 1994; Steven et al., 2014). Specifically, it is formulated as follows:

$$T5_{it} = \sum_{j=1}^{5} \frac{Sales_{ijt}}{Sales_{it}},$$

where the specific meaning of each variable is consistent with the previous formula. This measure is used in the robustness checks.

3.2.2. Analyst opinion divergence

We follow the literature and use the analyst forecast dispersion variable, *FDISP*, as a proxy for analyst opinion divergence. For additional robustness, we use analyst forecast error (*FERROR*) and optimism (*Optimism*) as alternative measures. We measure *FDISP* in three ways. Following Hope (2003a), Zhang (2006b) and Thomas (2002), we use the variance of analyst forecast values to measure *FDISP* in all three cases, but our three measurement methods are normalized differently. First, we construct $FDISP1$ using the method developed in the literature (Hope, 2003a; Johnson, 2004), which uses the average stock price of firm i over a year to reduce the influence of abnormal stock prices at a certain point. Thus, analyst forecast dispersion can be measured as

$$FDISP1_{it} = \frac{Std(Feps_{it})}{Mean(Price_{it})},$$

where $Std(Feps_{it})$ denotes the variance of analyst forecasts for firm i in year t and $Mean(Price_{it})$ denotes the average stock price of firm i over a fiscal year. A higher value for this variable indicates greater analyst forecast dispersion.

Second, following the classic approach adopted by Zhang (2006b), who uses the stock price of firm i at the end of year t to measure analyst forecast dispersion, we build $FDISP2$. Third, following Papakroni (2013), we define *FDISP*3, which is normalized by the actual value of firm *i* in year *t*. The three variables are calculated similarly to each other; among them, *FDISP*1 and *FDISP*2 are more widely used methods than *FDISP*3. Thus, we use *FDISP*1 and *FDISP*2 as the main explained variables, while *FDISP*3 is used to test the robustness of this study.

In line with the literature, in addition to *FDISP*, we adopt analyst forecast error (*FERROR*) as a second metric to measure analyst opinion divergence. We follow Brown and Kim (1991) and Lys and Soo (1995) and measure analyst forecast error as the difference between the average analyst forecast value and the actual value, and we scale it by the stock price at the beginning of year *t*, as follows:

$$FERROR_{it} = \frac{Abs[Mean(Feps_{it}) - Meps_{it}]}{BeginPrice_{it}},$$

where $Feps_{it}$ represents the analyst's forecast earnings per share of firm *i* in year *t* and $Mean(Feps_{it})$ is the mean of all analysts' forecast. $Meps_{it}$ denotes the actual earnings per share of firm *i* in year *t*. $BeginPrice_{it}$ denotes the share price at the beginning of year *t*. A larger value for this variable means that analysts are more inaccurate in their opinions.

3.3. Empirical model

We examine the association between analyst forecast dispersion and supplier concentration for the firm on which analysts focus by estimating the following panel regression model:

$$FDISP_{it} = \alpha_0 + \alpha_1 T5_{it} + \lambda X_{it} + \mu_i + \theta_t + \varepsilon_{it},$$

where $FDISP_{it}$ denotes analyst forecast dispersion for firm *i* in year *t*. It can be replaced with any proxy method discussed above, including *FERROR* and *Optimism*. Following Dhaliwal et al. (2016) and Itkowitz (2013), as our main explanatory variables, we select $T5_{it}$ and $T3_{it}$, which represent supplier concentration based on purchasing ratios. The vector *X* includes several control variables and we include firm and year fixed effects to control for firm factors and general business cycles.

The vector *X* includes some firm variables that impact analyst forecasts. We first include earnings per share volatility, *MepsVol*, because it is difficult for analysts to predict volatile earnings (Dichev and Tang, 2009). Hope (2003b) argues that losses can destabilize earnings, making earnings prediction complex for the analyst. Therefore, we add the variable *Loss* to our vector to control for this effect. Following Bae et al. (2008), we include a state ownership variable (*SOE*) to control for the effect of firm ownership (i.e., whether a firm is a state-owned enterprise [SOE]) on information disclosure. In addition, we add ownership concentration (*OwnCon*) to the control vector *X*, which is the sum of the shares held by the top 10 shareholders of the firm. Fidrmuc et al. (2006) and Jiang et al. (2011) find that ownership concentration has a U-shaped effect on the degree of information symmetry, thus affecting analyst forecasts. Furthermore, we include some firm fundamental variables to control for the firm's impact on analyst forecasts, including firm size (*Size*), leverage (*Lev*), return on assets (*ROA*) and firm age (*Age*). The specific variable definitions are reported in the Appendix.

3.4. Summary statistics

Panel A of Table 1 reports the descriptive statistics of the variables. The mean values of *FDISP*1, *FDISP*2 and *FDISP*3 are 0.022, 0.025 and 1.762, respectively. There is no significant difference between the first two variables because both are normalized by the share price. *FDISP*3, which is normalized with the actual value, is larger than the other proxy variables, as expected. The mean value of *FERROR* is 0.037. The mean value of the top five supplier concentration using the HHI method (*SupC*5) is 0.053, whereas that for the top three suppliers (*SupC*3) is 0.050. The average value of the purchasing ratio of the top five suppliers is 33.6%. In addition for firm characteristics, we find that *Size*, expressed as the average natural logarithm, is 22.163; *Lev* is 41.5%; *ROA* is 3.6%; *Age*, expressed as a natural logarithm. is 2.795; *MepsVol* is 0.252; and *OwnCon* is 58.7%. About 9.6% of the observations in the sample have a loss, and SOEs account for about 27.9% of the firms in the sample.

Table 1
Descriptive Statistics. Panel A of this table shows the sample's supplier concentration, analyst forecast dispersion or accuracy, and descriptive statistical results of other control variables. In contrast, Panel B shows the correlation coefficient matrix among variables. Specifically, supplier concentration variables are *SupC*5, *SupC*3, and *T*5, while analyst prediction dispersion or accuracy variables are *FDISP*1, *FDISP*2, *FDISP*3 and *FERROR*. The others are all control variables. Definitions of the variables are provided in the Appendix. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Summary Statistics

	Mean	S.D.	Q5	Q25	Median	Q75	Q95	N
FDISP1	0.022	0.019	0.002	0.008	0.016	0.031	0.069	11,642
FDISP2	0.025	0.021	0.002	0.008	0.018	0.034	0.078	11,642
FDISP3	1.762	3.432	0.091	0.293	0.660	1.540	7.466	11,642
FERROR	0.037	0.051	0.002	0.008	0.019	0.043	0.136	11,642
SupC5	0.053	0.083	0.002	0.009	0.022	0.058	0.220	11,642
SupC3	0.050	0.083	0.001	0.007	0.019	0.052	0.217	11,642
T5	0.336	0.194	0.090	0.193	0.294	0.445	0.732	11,642
Size	22.163	1.158	20.551	21.352	22.014	22.801	24.406	11,642
Lev	0.415	0.202	0.108	0.252	0.406	0.561	0.759	11,642
ROA	0.036	0.071	−0.059	0.016	0.038	0.068	0.127	11,642
Age	2.795	0.356	2.079	2.565	2.833	3.045	3.296	11,642
MepsVol	0.252	0.260	0.030	0.090	0.169	0.313	0.774	11,642
Loss	0.096	0.294	0.000	0.000	0.000	0.000	1.000	11,642
SOE	0.279	0.448	0.000	0.000	0.000	1.000	1.000	11,642
OwnCon	0.587	0.142	0.340	0.487	0.597	0.693	0.799	11,642

Panel B. Correlation Matrix

	SupC5	Size	Lev	ROA	Age	MepsVol	Loss	SOE	OwnCon	FDISP1
SupC5	1.00									
Size	−0.12***	1.00								
Lev	−0.02***	0.40***	1.00							
ROA	−0.05***	0.03***	−0.39***	1.00						
Age	0.03***	0.17***	0.18***	−0.11***	1.00					
MepsVol	0.01	0.09***	0.14***	−0.25***	0.00	1.00				
Loss	0.06***	−0.09***	0.24***	−0.68***	0.07***	0.31***	1.00			
SOE	0.03***	0.30***	0.31***	−0.09***	0.18***	−0.01**	0.06***	1.00		
OwnCon	−0.05***	0.15***	−0.17***	0.25***	−0.23***	0.04***	−0.18***	−0.12***	1.00	
FDISP1	−0.01	0.24***	0.24***	−0.26***	0.06***	0.30***	0.19***	0.04***	−0.12***	1.00

Panel B presents the Spearman correlation matrix for the main variables. As a result of the strong correlation between *FDISP* and *FERROR*, only one variable is included in the report. It can be seen that the correlation between *Loss* and *ROA* is relatively strong, with a correlation coefficient of –0.68. A higher value for *ROA* indicates stronger profitability. *Loss* is a dummy variable representing whether the firm's profit is negative. Thus, it is reasonable to observe a strong negative correlation between *Loss* and *ROA*. The correlations of the other control variables are modest, with correlation coefficients below 0.4, suggesting that the multicollinearity problem is relatively mild.

4. Empirical results

4.1. Baseline regression

Table 2 presents the associations between two measures of supplier concentration (*SupC*5 and *SupC*3) and two proxies for analyst opinion divergence (*FDISP*1 and *FDISP*2). The regression coefficients of *SupC*5 and *SupC*3 remain negative across all columns, indicating that analyst opinion dispersion decreases significantly as supplier concentration increases. This is consistent with H1a and is statistically significant at the 1% level.

Our results show that as *SupC*5 increases by one standard deviation, *FDISP1* and *FDISP2* decrease by 4.63% and 5.81%, respectively. The corresponding figures for *SupC*3 are 4.58% and 5.85%, respectively. These results are consistent with research indicating that a more concentrated supply chain can reduce information

Table 2
Supplier Concentration and Analyst Forecast Accuracy. This table presents the effect of supplier concentration on analysts' forecast behavior for a sample of China-listed firms from 2008 to 2019. The dependent variables are *FDISP*1 (the dispersion in analyst forecasts calculated by monthly average stock prices) and *FDISP*2 (the dispersion in analyst forecasts calculated by year-end stock prices) in year t. The main explanatory variables *SupC*5 and *SupC*3 are the supplier concentrations calculated as the sum of the squared sales-based purchasing ratios of the top five and three suppliers, following Campello and Gao (2017) and Patatoukas (2012). The control variables include *Size* (the natural logarithm of total assets), *Lev* (total liabilities to total assets), *ROA* (net income over total assets), *Age* (the natural logarithm of the age of the firm), *MepsVol* (the volatility of Meps), *Loss* (a dummy variable that is 1 when net profit is negative and 0 otherwise), *SOE* (a dummy variable, 1 for state-owned enterprises and 0 for others), and *OwnCon* (the total shareholding ratio of the top ten shareholders of the firm). The detailed variable definitions are presented in Table A1. All regressions include firm and year fixed effects. The robust t-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	SupC5		SupC3	
	(1) FDISP1	(2) FDISP2	(3) FDISP1	(4) FDISP2
SupC5	−0.0106***	−0.0147***		
	(−3.16)	(−3.89)		
SupC3			−0.0105***	−0.0148***
			(−3.15)	(−3.87)
Size	0.0054***	0.0075***	0.0054***	0.0075***
	(8.93)	(10.51)	(8.94)	(10.53)
Lev	−0.0048**	−0.0081***	−0.0048**	−0.0081***
	(−2.19)	(−3.18)	(−2.19)	(−3.18)
ROA	−0.0426***	−0.0508***	−0.0426***	−0.0508***
	(−8.66)	(−9.07)	(−8.67)	(−9.08)
Age	−0.0148***	−0.0186***	−0.0148***	−0.0186***
	(−3.92)	(−4.14)	(−3.92)	(−4.14)
MepsVol	0.0160***	0.0203***	0.0160***	0.0203***
	(12.54)	(13.63)	(12.54)	(13.64)
Loss	−0.0011	−0.0002	−0.0011	−0.0002
	(−1.27)	(−0.18)	(−1.27)	(−0.18)
SOE	−0.0016	−0.0026	−0.0016	−0.0026
OwnCon	(−0.33)	(−0.45)	(−0.33)	(−0.45)
	−0.0291***	−0.0357***	−0.0291***	−0.0357***
	(−(−8.80)	(−9.29)	(−8.81)	(−9.29)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	11,456	11,456	11,456	11,456
Number of Firms	2,134	2,134	2,134	2,134
Adjusted R^2	0.39	0.41	0.39	0.41

asymmetry and improve information exchange between firms (Hui et al., 2012; Costello, 2013; Cen et al., 2016). Our findings further suggest that viewing firms from the supply chain perspective can reduce analyst forecast dispersion.

The coefficient of *Size* is significant and positive, indicating that larger firms may have higher analyst forecast dispersion. The coefficients of *Lev*, *ROA* and *Age* are all negative, suggesting that analyst forecasts may be more consistent for firms with high leverage and high ROA, and for older firms. In addition, the coefficients of *MepsVol* are positive, which aligns with our prediction that analyst opinion divergence is greater for firms with higher earnings volatility. The coefficients of *OwnCon* are negative and significant in Columns (1)–(4), indicating that higher ownership concentration is associated with lower analyst forecast dispersion. Finally, the coefficients of *SOE* are negative for both *FDISP1* and *FDISP2*, suggesting that analyst forecasts are more consistent for SOEs than for non-SOEs.

4.2. Supplier concentration and information transparency

We explore the relationship between supplier concentration and firm information transparency by adopting four transparency indicators. As noted previously, we use two main proxy variables for supplier concentration, *SupC*5 and *SupC*3. Our indicators of firm information transparency can be divided into two measurement perspectives: information contained in the stock price and the transparency of accounting information.

For the first perspective, information contained in the stock price, we choose the *KV* index and stock price synchronization (*SYN*) as our two indicators. According to Kim and Verrecchia (2001), when a firm's information disclosure is sufficient, investors' reliance on trading volume information decreases, reducing the impact of trading volume on yields. This measure became what is known as the *KV* index, which reflects the market's dependence on trading volume information and the extent of corporate information disclosure. We expect the *KV* index to be negatively correlated with corporate transparency. Roll (1988) finds that R^2, a measure of stock price synchronization, can be used as a proxy for stock price information and that in a low-noise market, stock price change is driven by the individual information of the firm. Conversely, Lee and Liu (2011) find that in a high-noise market, stock price synchronization positively reflects the information efficiency of the market. Dasgupta et al. (2010) also observe that increased noise increases the uncertainty of stock price movement in the future and that stock price synchronization is positively correlated with information efficiency. Given the relative emergence of China as a market with high noise, we conclude that corporate transparency is positively correlated with stock price synchronization, based on recent research in the literature.

For the second perspective, the transparency of accounting information, we use accrued profit (*Accrual*) and earnings smoothness (*ES*) as our indicators. *Accrual* follows the calculation method of Bhattacharya et al. (2003) and Dhaliwal et al. (2012), with a higher value indicating a higher degree of earnings management and therefore a lower level of information transparency. *ES* is a measure of accounting opacity proposed by Bhattacharya et al. (2003). It captures the relationship between reported earnings and real earnings of listed firms. The smoother the earnings, the more likely is the firm to conceal fluctuations in its performance, resulting in less transparency. Therefore, a higher *ES* value indicates higher accounting information transparency. The specific calculation methods of these indicators are provided in the Appendix.

Table 3 illustrates the results of this section. Columns (1)–(8) correspond to the four indicators, *KV*, *SYN*, *Accrual* and *ES*, respectively. With the exception of *SYN*, the coefficients are positive and significant; the coefficient of *SYN* is negative and significant. The table shows that the results in Columns (1) and (2) are significant at the 1% level, those in Columns (7) and (8) are significant at the 5% level and those in Columns (3)–(6) are significant at the 10% level. *SYN* is positively correlated with transparency, whereas the other indicators are negatively correlated with transparency. These findings suggest that supplier concentration increases the firm's financial information transparency, thus reducing information asymmetry. Our results are consistent with those of McVay (2006) and Barua et al. (2010), who find that weak firms in the supply chain increase their core earnings and performance through classified transfer earnings management activities. Given this logic, firms with a greater concentration of suppliers are more likely to adjust their reporting data to minimize supply chain risk. Although adjusting the reporting data could make the firm's supply chain more secure, it generates an informational impediment for analysts.

Most indicators of information quality are derived from accounting information and stock prices. These indicators measure the quality of firm disclosure through accounting reports and public information available to investors. However, the supply chain perspective must be considered to conduct a comprehensive analysis as a basis for predicting outcomes. This is not easy for investors, and their difficulties in measuring supplier concentration and information quality may result in professional analysts having greater access to such information than the public. The implications of supplier concentration for the four transparency proxy indicators may be considered adverse, but overall they do not necessarily have a negative effect on the information quality of a firm because much of the supply chain information is not captured by the aforementioned indicators.

4.3. Firm and industry heterogeneity

We perform a cross-sectional analysis to examine the association between analyst forecast dispersion and supplier concentration, controlling for the effects of financial transparency, institutional ownership and product market competition. To do this, we divide the sample into subsamples based on high and low firm-level

Table 3
Information Transparency. This table presents the relationship between supplier concentration and information transparency for a sample of listed firms in China from 2008 to 2019. The dependent variables are *KV* (the coefficient of the impact of trading volume on yield, following Kim and Verrecchia (2001)), *SYN* (stock price synchronization calculated using R^2 statistic from the market model fromRoll (1988)), *Accrual* (the accrued profit used in calculating *FFIN*) and *ES* (earning Smooth is the relationship between reported earnings and true earnings of a listed firm (Bhattacharya, Daouk, and Welker, 2003)) in year t. The main explanatory variables *SupC*5 and *SupC*3 are the supplier concentrations calculated as the sum of the squared sales-based purchasing ratios of the top five and three suppliers (Campello and Gao, 2017; Patatoukas, 2012). The control variables include *Size* (the natural logarithm of total assets), *Lev* (total liabilities to total assets), *ROA*(net income over total assets), *Age* (the natural logarithm of the age of the firm), *MepsVol* (the volatility of *Meps*), *Loss* (a dummy variable that is 1 when net profit is negative and 0 otherwise), *SOE* (a dummy variable, 1 for state-owned enterprises and 0 for others), and *OwnCon* (the total shareholding ratio of the top ten shareholders of the firm). The detailed variable definitions are presented in Table A1. All regressions include firm and year fixed effects. The robust t-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1) KV	(2) KV	(3) SYN	(4) SYN	(5) Accrual	(6) Accrual	(7) ES	(8) ES
SupC5	0.0680***		−0.1085*		0.0657*		2.2266**	
	(3.44)		(−1.78)		(1.70)		(2.12)	
SupC3		0.0657***		−0.1038*		0.0653*		2.2654**
		(3.34)		(−1.67)		(1.66)		(2.14)
Size	−0.0296***	−0.0297***	0.0282***	0.0282***	0.0185***	0.0184***	−0.1780	−0.1788
	(−7.33)	(−7.34)	(5.17)	(5.19)	(5.14)	(5.13)	(−1.28)	(−1.29)
Lev	−0.0116	−0.0116	−0.1007***	−0.1007***	−0.2831***	−0.2831***	1.4022***	1.4037***
	(−0.87)	(−0.86)	(−6.06)	(−6.06)	(−20.60)	(−20.60)	(2.94)	(2.95)
ROA	0.0698***	0.0700***	−0.0986***	−0.0986***	0.3277***	0.3279***	−2.4313***	−2.4297***
	(3.26)	(3.26)	(−5.96)	(−5.96)	(6.80)	(6.80)	(−3.49)	(−3.49)
Age	−0.1028***	−0.1028***	−0.1252***	−0.1251***	0.0313	0.0313	−2.2349*	−2.2359*
	(−3.93)	(−3.93)	(−3.48)	(−3.47)	(1.27)	(1.28)	(−1.73)	(−1.73)
MepsVol	−0.0049	−0.0049	−0.0211***	−0.0211***	0.0364***	0.0364***	−4.3664***	−4.3665***
	(−0.88)	(−0.88)	(−2.74)	(−2.74)	(4.64)	(4.64)	(−15.77)	(−15.77)
Loss	0.0022	0.0022	−0.0051	−0.0051	0.0029	0.0029	−0.8797***	−0.8796***
	(0.63)	(0.63)	(−0.81)	(−0.82)	(0.58)	(0.58)	(−7.70)	(−7.70)
SOE	0.0153	0.0154	−0.0195	−0.0196	−0.0037	−0.0037	−1.7047	−1.7067
	(0.92)	(0.93)	(−0.60)	(−0.61)	(−0.15)	(−0.15)	(−1.38)	(−1.38)
OwnCon	0.3298***	0.3298***	−0.1375***	−0.1377***	0.0074	0.0074	−0.1085	−0.1071
	(18.65)	(18.65)	(−5.02)	(−5.03)	(0.42)	(0.43)	(−0.16)	(−0.16)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	12,378	12,378	10,791	10,791	11,239	11,239	6,923	6,923
Number of Firms	2,258	2,258	2,227	2,227	2,023	2,023	1,482	1,482
Adjusted R^2	0.57	0.57	0.34	0.34	0.09	0.09	0.55	0.55

financial transparency, institutional ownership and industry concentration. This allows us to conduct additional analyses.

4.3.1. Financial transparency

Richardson and Welker (2001) and Boone and White (2015) find that both financial transparency and the institutional shareholding ratio can influence analyst forecast behaviors. Financial transparency directly affects the availability of accounting information to analysts, with low transparency making it more difficult to obtain information and reducing the accuracy of their analysis. To exclude this influence on our results, we divide our sample according to the firms' degree of financial transparency. Specifically, we measure financial transparency using the dummy variable *FFIN*, which is based on publicly available information and almost no supply chain information. Using Dhaliwal et al. (2012) as a reference, we calculate each firm's scaled accruals (*ACCRUAL*) and allocate a value of one to firms if their *FFIN* is above the industry average; otherwise, we allocate them a value of zero.

Table 4 presents the results of the subsample regression analysis, displaying the coefficients of the explanatory variables only. Panel A reveals that supplier concentration influences analyst forecast dispersion for companies with low financial transparency, whereas the effect is not as evident for firms with high transparency. This is likely to occur because financial transparency has a greater impact on analyst forecast dispersion when the influence of suppliers is reduced. At low levels of transparency, supply chain information can improve the information environment and lead to suppliers providing more accurate forecasts to analysts. Supplier concentration has a dual effect on transparency in that it can inhibit financial information but help to mine supply chain information; thus, it is beneficial to further separate the results according to transparency. For the sub-

Table 4

Cross-Sectional Analysis. This table presents the association between supplier concentration and analyst forecast dispersion for subsamples of China-listed firms from 2008 to 2019. The sample is divided into two parts based on firm-level financial transparency (*FFIN*), institutional shareholding ratio (*InstHolder*), and industry concentration (*HHI*), respectively. Industry concentration is the product market competition measure calculated as the sum of the squared sales-based market shares. The dependent variables are *FDISP*1 and FDISP2 in year t. The main explanatory variables are *SupC*5 and *SupC*3. Other control variables include *Size* (the natural logarithm of total assets), Lev (total liabilities to total assets), *ROA* (net income over total assets), *Age* (the natural logarithm of the age of the firm), *MepsVol* (the volatility of *Meps*), Loss (a dummy variable that is 1 when net profit is negative and 0 otherwise), *SOE* (a dummy variable, 1 for state-owned enterprises and 0 for others), and *OwnCon* (the total shareholding ratio of the top ten shareholders of the firm). The detailed variable definitions are presented in Table A1. All regressions include firm and year fixed effects. The robust t-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Transparency

	Low		High	
	(1)	(2)	(3)	(4)
T5	−0.0541***		−0.0066	
	(−2.69)		(−0.35)	
T3		−0.0540***		−0.0067
		(−2.72)		(−0.34)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	4,699	4,699	4,946	4,946
Number of Firms	1,423	1,423	1,479	1,479
Adjusted R^2	0.41	0.41	0.36	0.36

Panel B. Institutional Ownership

	Low		High	
	(1)	(2)	(3)	(4)
T5	−0.0023		−0.0513***	
	(−0.15)		(−2.87)	
T3		−0.0024		−0.0510***
		(−0.15)		(−2.86)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	6,278	6,278	4,950	4,950
Number of Firms	1,345	1,345	1,021	1,021
Adjusted R^2	0.38	0.38	0.45	0.45

Panel C. Industry Concentration

	Low		High	
	(1)	(2)	(3)	(4)
T5	−0.0.389***		−0.0160	
	(−2.81)		(−0.98)	
T3		−0.0378***		−0.0174
		(−2.73)		(−1.09)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	6,297	6,297	4,591	4,591
Number of Firms	1,295	1,295	900	900
Adjusted R^2	0.39	0.39	0.40	0.40

samples with low transparency, the coefficients of *SupC*5 and *SupC*3 are –0.0541 and –0.0540, respectively, and they are significant at the 1% level. Comparing the coefficients to the baseline, we find that the absolute values of the coefficients in the subsamples exceed those of the original regression based on the full sample.

4.3.2. Institutional ownership

As external investors, institutions exert strong monitoring effects on firms when institutional ownership is high. Increased institutional ownership fosters the disclosure of accurate information by firms (Boone and White, 2015). The disclosure of accurate information enhances mutual trust among firms in the supply chain and facilitates stable, long-term cooperation. In addition, high institutional ownership improves the operational performance of firms (Lin and Fu, 2017), which in turn increases the probability of establishing long-term, stable partnerships. As the business ties among firms in the supply chain strengthen, firms exhibit an increasing degree of reliance on their suppliers. Consequently, we contend that our main results will be more pronounced when institutional ownership is higher.

To evaluate a firm's institutional ownership, we divide our sample using a continuous variable, *InstHolder*, which is the percentage of shares held by institutional investors. In Table 4, Panel B presents the association between supplier concentration and analyst forecast behavior under different levels of institutional shareholding ratios. Columns (3) and (4) show that for firms with high institutional ownership, supplier concentration has a significant effect on analyst forecast behavior, as evidenced by the significant coefficients at the 1% level. In contrast, the effect is not evident for firms with a low institutional shareholding ratio. For the subsample with high institutional shareholding, the coefficients of *SupC*5 and *SupC*3 are –0.0513 and –0.0510, respectively, and the absolute values of the coefficients exceed those from the baseline results, confirming our prediction. High institutional shareholding is likely to improve certain information environments due to the supervisory role played by institutional investors, which results in greater standardization of firm behavior and more apparent supply chain functions.

4.3.3. Industry concentration

A firm's ability to influence its suppliers may depend on its bargaining power, which we measure using the degree of industry concentration. A lower degree of industry concentration indicates that the industry is more competitive, weakening the firm's bargaining power. This reduces the firm's advantage in transactions and increases its likelihood of being influenced by suppliers. Following Hou and Robinson (2006), we use *HHI* to measure industry concentration. *HHI* ranges from zero to one, with higher values indicating a higher degree of industry concentration and lower levels of competition.

Panel C of Table 4 shows the results for *HHI*. We observe that as industry concentration increases, the impact of supplier concentration on analyst forecast behavior becomes less significant. For firms with low industry concentration, the coefficients of *SupC*5 and *SupC*3 are –0.0389 and –0.0378, respectively, and both are significant at the 1% level. These values are higher than those of the baseline regression, which aligns with our expectations and supports our conclusion. When industry concentration is low, firms have limited bargaining power, and suppliers control over the firms increases. As a result, the likelihood that firms will compromise with suppliers to maintain business relations increases (Dyer, 1996). In this way, supply chains can constrain firms, and we find that the effect is significant.

4.4. Plausible channels

The number of analyst followers is an important indicator influencing analyst forecast behavior (Irani and Karamanou, 2003). Studies show that firms with more analyst followers are associated with less divergence in analyst forecasts (Irani and Karamanou, 2003). From the supply chain perspective, firms with high supplier concentration have a more straightforward supply chain structure than those with low supplier concentration, making it easier for analysts to track their entire chain (Hui et al., 2012; Cen et al., 2016). This increases analyst attention, as such firms are unlikely to manipulate information (Lang et al. 2004). Thus, we expect firms with high supplier concentration to attract many analyst followers, which is associated with improvements in analyst forecast behavior.

In summary, analyst following is expected to be an essential intermediary indicator in our analysis. Furthermore, firms are incentivized to align their earnings management with analyst forecasts (Abarbanell and Lehavy, 2003; Hunton et al., 2006), which decreases analyst forecast dispersion. Both of these effects have an impact on analyst forecasts. This section performs a two-step mediation analysis to identify the potential mechanism through which supplier concentration influences analyst forecasts. Specifically, we use the following standard method:

$$M_{it} = \alpha SupC5_{it} + \lambda X_{it} + \mu_i + \theta_t + \varepsilon_{it}$$

and

$$FDISP_{it} = \alpha M_{it} + \lambda X_{it} + \mu_i + \theta_t + \varepsilon_{it}$$

where $FDISP_{it}$ denotes analyst forecast dispersion for firm i in year t and M_{it} denotes the mediating variables. The first step is to study the relationship between the supplier concentration of the firm and analysts following earnings management. In the second step, we regress analyst forecast dispersion on supplier concentration, the mediator and other control variables.

We use the number of analysts covering the firm in a year, which can be obtained directly from the CSMAR database, and take the natural logarithm as a proxy for analyst following. We employ the modified Jones model proposed by Bartov et al. (2000) to measure earnings management, and calculate indicators such as *DisAcc* (accrued earnings management). A higher index indicates higher levels of earnings management, which can reduce analyst forecast dispersion. The specific calculation method is provided in the Appendix.

Table 5 presents the results of the mediation analyses for two variables: supplier concentration (*SupC*5) and analyst forecast dispersion (*FDISP*1). Columns (1) and (2) replicate our regression results for the mediating and independent variables. The analysis in Column (1) reveals that there is a positive and statistically significant relationship between analyst following (*Follow*) and *SupC*5. This finding suggests that firms with a higher concentration of suppliers tend to draw more analysts to follow them. This could result from the fact that, often, the costs of analysts tracking the supply chain is lower for firms with a higher concentration of suppliers, and the clear structure makes these firms easy to analyze. As a result, analysts are more likely to keep a closer eye on these firms than on their counterparts.

Column (2) shows that a higher *SupC*5 is positively correlated with a higher *DisAcc*, and this result is significant at the 5% level. This suggests that firms may engage in earnings management to meet the expectations of major suppliers and to maintain their trading relationships. The results for the remaining variables are similar.

We report the regression results of the independent variables and the mediating variables in Columns (3) and (4) to examine the existence of two potential channels. Our findings reveal that the coefficient of *Follow* and *DisAcc* remain negative and statistically significant at the 1% level, aligning with our prediction. These results suggest that *Follow* and *DisAcc* potentially serve as two channels through which supplier concentration influences analyst forecast behavior.

5. Robustness checks

5.1. Endogeneity issues

5.1.1. Instrumental variable regression

Our baseline results may be affected by potential endogeneity issues. We may not have considered some firm characteristics that could create a false correlation between supplier concentration and analyst forecast dispersion. In addition, analysts' research can influence firms' behavior, which could result in reverse causality issues. To address these potential issues, we continue to estimate the impact of supplier concentration on analyst forecast dispersion.

We estimate a two-stage least-squares model with IVs, in which *SupC*5 and *SupC*3 are regarded as endogenous variables. Following Dhaliwal et al. (2016), we choose the lagged industry average of supplier concentration as an IV, *ASupC*5 and *ASupC* 3. *ASupC*5 is the equally weighted average of *SupC*5 for all firms in the same industry, excluding the focal firm, over a fiscal year. *ASupC*3 is computed similarly. In addition, stud-

Table 5
Possible Mechanism. This table presents the mediating role of analyst following and accrued earnings management in the association between supplier concentration and analyst forecast dispersion for a sample of China-listed firms from 2008 to 2019. The dependent variables in Columns (1) and (2) are *Follow* and *DisAcc*. *Follow* is the natural logarithm of the number of analysts or teams following the firm in the same year. *DisAcc* is accrued earnings management calculated by the Modified Jones Model (Bartov, Gul, and Tsui, 2000). The main explanatory variable *SupC5* is the top five supplier concentration constructed with the HHI method. The dependent variables in Columns (3) and (4) are all *FDISP1* in year t, which is the proxy of analyst forecast dispersion. The explanatory variables are *Follow* and *DisAcc*. Other control variables include *Size* (the natural logarithm of total assets), *Lev* (total liabilities to total assets), *ROA* (net income over total assets), *Age* (the natural logarithm of the age of the firm), *MepsVol* (the volatility of *Meps*), *Loss* (a dummy variable that is 1 when net profit is negative and 0 otherwise), *SOE* (a dummy variable, 1 for state-owned enterprises and 0 for others), and *OwnCon* (the total shareholding ratio of the top ten shareholders of the firm). All regressions include firm and year fixed effects. The robust t-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1) Follow	(2) DisAcc	(3) FDISP	(4) FDISP
SupC5	−0.0069***	0.0221***		
	(2.70)	(2.07)		
Follow			−0.0026***	
			(−16.64)	
DisAcc				−0.0117***
				(−5.74)
Size	0.5758***	0.0043***	0.0045***	0.0032***
	(17.38)	(2.66)	(12.79)	(9.35)
Lev	−0.4230***	0.0005	−0.0049***	−0.0033***
	(−3.75)	(0.09)	(−3.77)	(−2.58)
ROA	2.4764***	−0.0518***	−0.0354***	−0.0446***
	(11.34)	(−3.75)	(−11.70)	(−14.79)
Age	−0.3444*	−0.0027	0.0040**	0.0044***
	(−1.83)	(−0.29)	(2.54)	(2.79)
MepsVol	0.0648	0.0161***	0.0122***	0.0121***
	(1.23)	(5.48)	(18.65)	(18.52)
Loss	−0.0117	0.0129***	−0.0005	−0.0005
	(−0.33)	(5.37)	(−0.99)	(−0.93)
SOE	−0.0145	−0.0106	0.0017	0.0013
	(−0.08)	(−1.18)	(0.85)	(0.62)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	12,444	12,444	22,611	22,611
Number of Firms	2,262	2,262	3,097	3,097
Adjusted R^2	0.64	0.14	0.39	0.38

ies indicate that lagged independent variables can be used as IVs (Doytch and Uctum, 2011). Therefore, we select lagged supplier concentration as one of our IVs. Due to sample size limitations, we select the variable lagged by one period as an IV to reduce the loss of observations. Typically, supplier concentration remains relatively stable over time, so a firm's current supplier concentration is correlated with the previous level. The exclusion restriction is satisfied by these two IVs, with any direct relationship between them and the other variables in the current year avoided. Thus, these two variables can be used as IVs.

Table 6 presents the results of the IV regressions. Columns (1) and (2) present the first-stage results. We use the sum of the purchasing ratio of the top five suppliers (*SupC5*) or the top three suppliers (*SupC3*) as the dependent variable, with two IVs (*L.SupC5* and *L.ASupC5* or *L.SupC3* and *L.ASupC3*) and other control variables as the main explanatory variables. The results show that both *L.SupC5* and *L.ASupC5* are significant and positively correlated with *SupC5*, which aligns with our expectation that a firm's supply chain structure has some continuity and is relevant to its industry. The results for *SupC3* are similar. Furthermore, the Cragg–Donald Wald F statistics in these two regressions are 260.71 and 251.36, respectively, indicating that these two IVs do not suffer from weak IV issues. The Hansen J test confirms that our chosen IVs satisfy the exclusion restriction.

Table 6
Instrumental Variable Regression. The table presents the elimination of endogeneity with the instrumental variable method for a sample of China-listed firms from 2008 to 2019. The instrumental variables are *ASpC*5 (the equally-weighted average of *SupC*5 of firms in the industry and a fiscal year excluding the focal firm from Dhaliwal et al. (2016)) and *SupC*5 (the supplier concentration of the top five suppliers) in year t − 1. The instrumental variables for *SupC*3 are similar. The dependent variables are *FDISP*1 and *FDISP*2 in year t. The control variables include *Size* (the natural logarithm of total assets), *Lev* (total liabilities to total assets), *ROA* (net income over total assets), *Age* (the natural logarithm of the age of the firm), *MepsVol* (the volatility of Meps), *Loss* (a dummy variable that is 1 when net profit is negative and 0 otherwise), *SOE* (a dummy variable, 1 for state-owned enterprises and 0 for others), and *OwnCon* (the total shareholding ratio of the top ten shareholders of the firm), which is same with the baseline. The detailed variable definitions are presented in Table A1. All regressions include firm and year fixed effects. The robust t-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	First Stage			Second Stage		
	(1) SupC5	(2) SupC3	(3) FDISP1	(4) FDISP2	(5) FDISP1	(6) FDISP2
L.SupC5	0.2468***					
	(13.20)					
L.ASupC5	0.1259**					
	(2.04)					
L.SupC3		0.2423***				
		(12.93)				
L.ASupC3		0.1175*				
		(1.88)				
SupC5			−0.0677**	−0.0727**		
			(−2.23)	(−2.09)		
SupC3					−0.0713**	−0.0762**
					(−2.26)	(−2.12)
Size	−0.0056***	−0.0052***	0.0056***	0.0075***	0.0056***	0.0075***
	(−4.08)	(−3.80)	(7.68)	(8.96)	(7.74)	(9.03)
Lev	0.0043	0.0040	−0.0045*	−0.0078***	−0.0045*	−0.0078***
	(0.86)	(0.83)	(−1.81)	(−2.71)	(−1.81)	(−2.71)
ROA	0.0015	−0.0002	−0.0365***	−0.0440***	−0.0366***	−0.0441***
	(0.17)	(−0.02)	(−6.92)	(−7.30)	(−6.95)	(−7.33)
Age	−0.0040	−0.0045	−0.0180***	−0.0213***	−0.0180***	−0.0214***
	(−0.46)	(−0.53)	(−3.77)	(−3.94)	(−3.78)	(−3.95)
MepsVol	0.0039*	0.0038*	0.0171***	0.0213***	0.0171***	0.0213***
	(1.95)	(1.94)	(12.37)	(13.29)	(12.38)	(13.31)
Loss	−0.0006	−0.0007	−0.0011	−0.0001	−0.0011	−0.0001
	(−0.38)	(−0.48)	(−1.19)	(−0.06)	(−1.20)	(−0.08)
SOE	0.0264***	0.0264***	0.0011	0.0003	0.0012	0.0005
	(3.05)	(3.08)	(0.17)	(0.05)	(0.18)	(0.06)
OwnCon	−0.0064	−0.0065	−0.0313***	−0.0380***	−0.0314***	−0.0381***
	(−0.94)	(−0.97)	(−8.33)	(−8.87)	(−8.35)	(−8.89)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	10,640	10,640	9,761	9,761	9,761	9,761
Number of Firms	2,181	2,181				
Cragg-Donald Wald F statistic			260.71	260.71	251.36	251.36
Hansen J statistic (p-value)			0.50	0.62	0.55	0.68

The second-stage regression results, shown in Columns (3)–(6), indicate that analyst forecast dispersion (*FDISP*1 or *FDISP*2) is the main explanatory variable. We find that the coefficients of *SupC*5 and *SupC*3 are both negatively correlated and significant at the 5% level, consistent with our baseline. The p values for the Hansen's J statistic are greater than 0.50, so we cannot reject the joint null hypothesis that our IVs are unrelated to the error term. This suggests that our primary findings remain robust after appropriately addressing endogeneity concerns through IV regression.

Table 7

Propensity Score Matching. This table presents the effect of supplier concentration on analysts' forecast behavior for a sample of China-listed firms from 2008 to 2019. Panel A reports insignificant differences in covariates between the treated and control groups after matching, and Panel B reports the regression results of the matched samples. The matched sample is constructed using the propensity score matching technique. The firms with the above-median supplier concentration are the treatment group, and the other firms are the control group. The one-to-one nearest neighborhood matching algorithm is applied without replacement using firm size, firm age, leverage, return on assets, EPS volatility, earnings losses, state ownership, and ownership concentration as the matching covariates. We also need the matched firms from the same industry and fiscal year. The dependent variables are *FDISP*1 and *FDISP*2 in year t. The main explanatory variables are *SupC*5 and *SupC*3. Other control variables include *Size* (the natural logarithm of total assets), *Lev* (total liabilities to total assets), *ROA* (net income over total assets), *Age* (the natural logarithm of the age of the firm), *MepsVol* (the volatility of Meps), *Loss* (a dummy variable that is 1 when net profit is negative and 0 otherwise), *SOE* (a dummy variable, 1 for state-owned enterprises and 0 for others), and *OwnCon* (the total shareholding ratio of the top ten shareholders of the firm). The detailed variable definitions are presented in Table A1. All regressions include firm and year fixed effects. The robust t-statistics clustered by the firm and year are reported in parentheses.***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Covariate Balance

	Sample	Control	Treatment	Diff	T-stats
size	Full	22.07	21.77	0.29	18.43
	Matched	22.03	22.04	−0.01	−0.04
Lev	Full	0.45	0.40	0.06	19.27
	Matched	0.40	0.40	−0.00	−0.06
ROA	Full	0.04	0.03	0.00	3.53
	Matched	0.04	0.04	0.00	0.03
Age	Full	2.78	2.81	−0.03	−7.21
	Matched	2.79	2.79	−0.00	−0.01
Loss	Full	0.24	0.26	−0.02	−4.76
	Matched	0.25	0.25	−0.00	−0.07
SOE	Full	0.10	0.12	−0.01	−3.57
	Matched	0.10	0.10	−0.00	−0.04

Panel B: Matched Sample

	(1) FDISP1	(2) FDISP2	(3) FDISP1	(4) FDISP2
SupC5	−0.0093***	−0.0143***		
	(−2.60)	(−3.53)		
SupC3			−0.0094**	−0.0146***
			(−2.54)	(−3.47)
Size	0.0057***	0.0077***	0.0060***	0.0081***
	(7.77)	(8.99)	(7.24)	(8.28)
Lev	−0.0045*	−0.0080***	−0.0045	−0.0084**
	(−1.75)	(−2.64)	(−1.54)	(−2.38)
ROA	−0.0385***	−0.0463***	−0.0422***	−0.0485***
	(−6.75)	(−7.05)	(−6.25)	(−6.18)
Age	−0.0091**	−0.0135**	−0.0107**	−0.0147**
	(−1.98)	(−2.47)	(−2.07)	(−2.37)
MepsVol	0.0149***	0.0191***	0.0166***	0.0210***
	(9.58)	(10.48)	(9.52)	(9.98)
Loss	−0.0011	−0.0000	−0.0013	−0.0004
	(−1.01)	(−0.04)	(−1.06)	(−0.30)
SOE	−0.0024	−0.0035	−0.0055	−0.0074
	(−0.38)	(−0.46)	(−0.92)	(−1.03)
OwnCon	−0.0310***	−0.0385***	−0.0289***	−0.0358***
	(−7.99)	(−8.75)	(−6.57)	(−7.07)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	7,331	7,331	5,467	5,467
Number of Firms	1,746	1,746	1,417	1,417
Adjusted R^2	0.39	0.40	0.40	0.40

5.1.2. Propensity score matching

We address the concern that our baseline results may be driven by systematic differences between firms with high or low levels of supplier concentration through PSM. Specifically, we define the firms with an above-median level of supplier concentration as the treatment group, and the remaining firms as the control group. Then, we estimate a logit model with firm *Size*, *Age*, *Lev*, *ROA*, *MepsVol*, *Loss*, *SOE* and *OwnCon* as matching covariates to obtain the propensity scores. These control variables are consistent with those in our baseline regression. We consider the matched firms from the same industry and fiscal year, following the classification method published by the CSRC in 2012. Applying the one-to-one nearest neighbor matching technique without replacement, the matched sample consists of 7,331 and 5,467 firm-year observations.

The covariate balance test in Panel A of Table 7 reveals insignificant differences in covariates between the treatment and control groups after PSM. Fig. 1 confirms that PSM successfully minimizes the systematic difference in the firm characteristics of the matched sample. To conserve space, we show the test results only for *SupC*5 here. The results are quantitatively similar for *SupC*3.

Panel B of Table 7 presents the results of the regression performed on the matched sample, with *FDISP*1 or *FDISP*2 as the primary explanatory variable. We find that the coefficients of *SupC*5 and *SupC*3 are negative in all columns, with Columns (1), (2) and (4) being significant at the 1% level and Column (3) at the 5% level. The magnitude of the coefficients is similar to that of our baseline estimation when the PSM technique is implemented. Thus, our main results remain unchanged after matching, suggesting that the relationship between analyst forecast behavior and supplier concentration is independent of the systemic characteristics of firms. Therefore, our results are robust when PSM is employed.

5.2. Alternative variable definitions

To assess the strength of our study findings, we substitute the proxy for analyst opinion divergence in our baseline model with the alternatives *FDISP*3 and *FERROR*. As noted previously, *FDISP*3 is an index of analyst forecast dispersion and *FERROR* is a measure of analyst forecast error. Thus, we use these variables in a regression analysis as a robustness check.

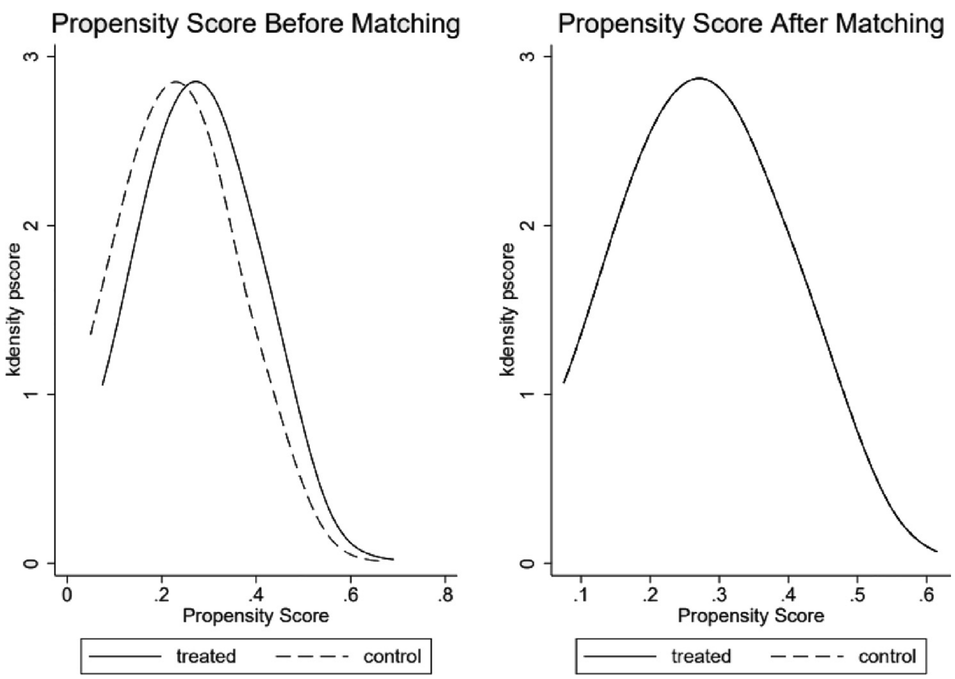

Fig. 1. Propensity Score Before and After Matching.

Table 8 presents the results of the *SupC*5 and *SupC*3 models. For *SupC*5, the regression coefficients of *FDISP*3 and *FERROR* are all negative and significant at the 10% level. Similarly, for *SupC*3, the regression coefficients of the explanatory variables are all negative and significant at the 10% level. These results demonstrate that supplier concentration significantly improves analyst forecast dispersion. The improvement in supplier concentration appears to affect analyst forecast behavior. We speculate that this occurs because of the information contained in the supply chain, which can be beneficial to analyst forecasts. With a centralized supply chain, this information becomes readily accessible and, therefore, it can improve forecast accuracy. In addition, supplier concentration often implies risk, tempering analysts' optimism. These results are consistent with those of our baseline regression, demonstrating the robustness of our findings.

We further test the robustness of our results by replacing the explained variable *HHI* with *T*5, the sum of the purchasing ratio of the top five suppliers, as explained previously. We conduct a regression analysis with our proxies for analyst opinion divergence (*FDISP*1, *FDISP*2, *FDISP*3 and *FERROR*), enabling us to effectively assess the robustness of our results.

Table 9 presents the regression results and reveals that all of the coefficients are negative and significant. *FDISP*1 and *FDISP*2 (Columns (1) and (2), respectively) are significant at the 1% level, whereas *FDISP*3 (Col-

Table 8
Alternative Analyst Forecast Dispersion and Error. This table presents the association of supplier concentration with an alternative measure of analysts' forecast behavior for a sample of China-listed firms from 2008 to 2019. The dependent variables are *FDISP*3 (the dispersion in analyst forecasts calculated by the actual value (Papakroni, 2013)) and *FERROR* (the accuracy in analyst forecasts calculated by the share price of the beginning of the year, following Brown and Kim (1991), and Lys and Soo (1995)). The main explanatory variables are *SupC*5 and *SupC*3, which are the supplier concentrations of top five and three suppliers, following Campello and Gao (2017) and Patatoukas (2012). The control variables include *Size* (the natural logarithm of total assets), *Lev* (total liabilities to total assets), *ROA* (net income over total assets), *Age* (the natural logarithm of the age of the firm),*MepsVol* (the volatility of Meps), *Loss* (a dummy variable that is 1 when net profit is negative and 0 otherwise), *SOE* (a dummy variable, 1 for state-owned enterprises and 0 for others), and *OwnCon* (the total shareholding ratio of the top ten shareholders of the firm). The detailed variable definitions are presented in Table A1. All regressions include firm and year fixed effects. The robust t-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	SupC5		SupC3	
	(1) FDISP3	(2) FERROR	(3) FDISP3	(4) FERROR
SupC5	−1.5622*	−0.0122*		
	(−1.94)	(−1.85)		
SupC3			−1.5287*	−0.0122*
			(−1.91)	(−1.87)
Size	0.2500**	0.0038***	0.2512**	0.0038***
	(2.14)	(2.59)	(2.15)	(2.60)
Lev	−0.6413	−0.0020	−0.6425	−0.0020
	(−1.50)	(−0.42)	(−1.50)	(−0.42)
ROA	−7.7399***	−0.3441***	−7.7432***	−0.3441***
	(−7.01)	(−26.05)	(−7.01)	(−26.05)
Age	−1.1994*	−0.0125*	−1.1990*	−0.0125*
	(−1.70)	(−1.72)	(−1.70)	(−1.72)
MepsVol		0.0616***	0.4580*	0.0616***
	0.4586*			
	(1.90)	(18.64)	(1.90)	(18.63)
Loss	−2.5154***	0.0239***	−2.5156***	0.0239***
	(−8.41)	(10.26)	(−8.41)	(10.26)
SOE	0.3372	0.0002	0.3369	0.0002
	(0.30)	(0.02)	(0.30)	(0.02)
OwnCon	−4.1139***	−0.0434***	−4.1141***	−0.0434***
	(6.17)	(−5.97)	(6.17)	(−5.97)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	11,462	12,437	11,462	12,437
Number of Firms	2,134	2,262	2,134	2,262
Adjusted R^2	0.20	0.64	0.20	0.64

umn (3)) is significant at the 5% level and *FERROR* (Column (4)) is significant at the 10% level. These results are in line with the findings for *SupC*5 and *SupC*3 in the baseline regression, lending further support to the robustness of the conclusions drawn in this study.

5.3. Additional control variables

We investigate the robustness of our research results by adding control variables to our basic model. The results of Table 10 show that although we select *FDISP*1 and *SupC*5 for reporting, the remaining variable combinations are consistent with these representative variables.

Column (1) of Table 10 provides our baseline result for comparison with the results after adding the control variables. We add two control variables to our baseline regression equation, *FFIN* and *InstHolder*, with the results reported in Column (2). Boone and White (2015) show that financial transparency directly affects analyst forecast accuracy and that institutional ownership influences information transparency as a result of agency problems and analyst forecast behavior. Therefore, we add these two indicators as control variables and use them for subsample analyses.

In Column (2) of Table 10, we add a non-financial metric to the regression results, analysts' forecast horizon (*Horizon*), which measures the time between the forecast date and the earnings announcement date. De Bondt and Thaler (1990) and O'Brien (1990) find that as the forecast horizon increases, analyst forecast error

Table 9
Alternative Supplier Concentration Measures. This table presents the association of supplier concentration on an alternative measure of analysts' forecast behavior for a sample of China-listed firms from 2008 to 2019. The dependent variables are *FDISP*1 (the dispersion in analyst forecasts calculated by monthly average stock prices), *FDISP*2 (the dispersion in analyst forecasts calculated by year-end stock prices), *FDISP*3 (the dispersion in analyst forecasts calculated by the actual value (Papakroni, 2013)) and *FERROR* (the accuracy in analyst forecasts calculated by the share price of the beginning of the year, following Brown and Kim (1991) and Lys and Soo (1995)). The main explanatory variable *T*5 is the total purchasing share of the top five suppliers. The control variables include *Size* (the natural logarithm of total assets), Lev (total liabilities to total assets), *ROA* (net income over total assets), *Age* (the natural logarith of the age of the firm), *MepsVol* (the volatility of Meps), *Loss* (a dummy variable that is 1 when net profit is negative and 0 otherwise), *SOE* (a dummy variable, 1 for state-owned enterprises and 0 for others), and *OwnCon* (the total shareholding ratio of the top ten shareholders of the firm). The detailed variable definitions are presented in Table A1. All regressions include firm and year fixed effects. The robust t-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1) FDISP1	(2) FDISP2	(3) FDISP3	(4) FERROR
T5	−0.0048***	−0.0065***	−0.3657**	−0.0044*
	(−2.83)	(−3.40)	(−2.17)	(−1.75)
Size	0.0054***	0.0074***	0.0890	0.0043***
	(8.74)	(10.31)	(1.39)	(4.66)
Lev	−0.0048**	−0.0082***	−0.5312**	−0.0106***
	(−2.19)	(−3.19)	(−2.40)	(−3.41)
ROA	−0.0425***	−0.0507***	−4.8732***	−0.1538***
	(−8.64)	(−9.04)	(−8.76)	(−22.23)
Age	−0.0150***	−0.0188***	−0.7014**	−0.0147***
	(−3.96)	(−4.18)	(−2.03)	(−2.72)
MepsVol	0.0159***	0.0202***	0.2868**	0.0307***
	(12.49)	(13.57)	(2.21)	(15.37)
Loss	−0.0011	−0.0001	−1.5877***	0.0214***
	(−1.25)	(−0.15)	(−12.26)	(15.58)
SOE	−0.0016	−0.0026	0.3315	0.0063
	(−0.33)	(−0.45)	(0.58)	(1.12)
OwnCon	−0.0290***	−0.0355***	−2.6216***	−0.0363***
	(−8.78)	(−9.25)	(−7.67)	(−7.39)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	11,456	11,456	11,462	12,437
Number of Firms	2,134	2,134	2,134	2,262
Adjusted R^2	0.39	0.41	0.27	0.55

Table 10

Additional Control Variables. This table presents the association of supplier concentration on analysts' forecast behavior with different models for a sample of China-listed firms from 2008 to 2019. The dependent variables are *FDISP*1 (the dispersion in analyst forecasts calculated by monthly average stock prices) in year t. The main explanatory variable *SupC*5 is the supplier concentration measure calculated as the sum of the squared sales-based purchasing ratios of the top five suppliers. The main control variables include *Size* (the natural logarithm of total assets), *Lev* (total liabilities to total assets), *ROA* (net income over total assets), *Age* (the natural logarithm of the age of the firm), *MepsVol* (the volatility of *Meps*), *Loss* (a dummy variable that is 1 when net profit is negative and 0 otherwise), *SOE*(a dummy variable, 1 for state-owned enterprises and 0 for others), and *OwnCon* (the total shareholding ratio of the top ten shareholders of the firm). The control variables in Column (2) add *FFIN* (the firm-level financial transparency) and *InstHolder* (institutional shareholding ratio). The control variables in Column (3) add *Horizon* (the range of analysts' forecast). The control variables in Column (4) add *BM* (book-to-market value), *CF* (the ratio of cash flow), and *FA* (the ratio of fixed assets). The detailed variable definitions are presented in Table A1. All regressions include firm and year fixed effects. The robust t-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1) FDISP1	(2) FDISP1	(3) FDISP1	(4) FDISP1
SupC5	−0.0106***	−0.0114***	−0.0109***	−0.0093**
	(−3.16)	(−3.35)	(−2.80)	(−2.34)
FFIN		−0.0007*	−0.0010***	−0.0012***
		(−1.95)	(−3.02)	(−3.49)
InstHolder		−0.0002***	−0.0003***	−0.0002***
		(−8.07)	(−8.71)	(−6.09)
Horizon			−0.0016**	−0.0026***
			(−2.52)	(−4.08)
BM				0.0221***
				(10.85)
CF				−0.0082***
				(−2.93)
FA				0.0110***
				(2.97)
Size	0.0054***	0.0066***	0.0067***	0.0045***
	(8.93)	(9.60)	(9.01)	(5.13)
Lev	−0.0048**	−0.0085***	−0.0111***	−0.0103***
	(−2.19)	(−3.55)	(−4.10)	(−3.76)
ROA	−0.0426***	−0.0402***	−0.0590***	−0.0419***
	(−8.66)	(−7.98)	(−9.22)	(−6.69)
Age	−0.0148***	−0.0142***	−0.0107**	−0.0096**
	(−3.92)	(−3.07)	(−2.16)	(−2.02)
MepsVol	0.0160***	0.0178***	0.0205***	0.0216***
	(12.54)	(12.79)	(13.00)	(13.85)
Loss	−0.0011	−0.0007	−0.0012	−0.0005
	(−1.27)	(−0.81)	(−1.21)	(−0.47)
SOE	−0.0016	−0.0016	−0.0002	−0.0005
	(−0.33)	(−0.34)	(−0.03)	(−0.11)
OwnCon	−0.0291***	−0.0068	−0.0040	−0.0132***
	(−8.80)	(−1.55)	(−0.85)	(−2.74)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	11,456	10,333	8,722	8,493
Number of Firms	2,134	1,920	1,763	1,751
Adjusted R^2	0.39	0.40	0.42	0.44

also increases, which is probably because of the amount of information available for forecasting. In addition, we add three financial indicators to the control variables: book-to-market ratio (*BM*), cash holding ratio (*CF*) and fixed assets ratio (*FA*). The results of these regressions are reported in Columns (3) and (4), respectively. The definitions of these control variables are provided in the Appendix.

The regression coefficients of *SupC*5 in Table 10 are all negative and significant. The coefficients in Columns (1), (2) and (3) are significant at the 1% level and that in Column (4) is significant at the 5% level. Furthermore, the range of the regression coefficients is reasonable, and the direction of the newly added control variables is consistent with the literature (DeFond and Hung, 2003; Wang and Alam, 2007). This suggests that our findings are robust to alternative model specifications.

6. Further discussion

6.1. Analyst attention

The analysis above reveals that supplier concentration is receiving increasing attention from analysts. To further investigate this phenomenon, we construct four indicators: analyst attention based on research reports (*RepAtt*), the proportion of expert analysts (*BePro*), the proportion of star analysts (*BeStar*) and the number of star analysts (*StarNum*). *RepAtt* measures the number of research reports analyzing the firm i in year t. *BePro* and *BeStar* indicate which indicator of supplier concentration has the greatest effect on increasing analyst attention. To identify the expert and star analysts, we use the length of working years, ranking all analysts and defining those with above-average working years as experts. Because of missing values in the star analyst data, we use a tobit model for the regression analysis.

Table 11
Further Exploration of Analyst Attention. The table presents the impact of supplier concentration on the component of analysts attracted for a sample of China-listed firms from 2008 to 2019. Tobit regression is used for the regression. Panel A shows the influence of analyst professionalism and reports attention. The dependent variables are *RepAtt* (research newspaper attention) and *BePro* (the proportion of expert analysts among analysts) in year t. Panel B shows the influence of star analysts. The dependent variables are *BeStar* (the proportion of star analysts among analysts) and *StarNum* (the number of star analysts among analysts) in year t. The main explanatory variables are *SupC*5 and *SupC*3, which are the supplier concentrations calculated as the sum of the squared sales- based purchasing ratios of the top five and three suppliers, following Campello and Gao (2017) and Patatoukas (2012). The control variables include *Size* (the natural logarithm of total assets), *Lev*(total liabilities to total assets), *ROA* (net income over total assets), *Age* (the natural logarithm of the age of the firm), *MepsVol*(the volatility of *Meps*), *Loss* (a dummy variable that is 1 when net profit is negative and 0 otherwise), *SOE* (a dummy variable, 1 for state-owned enterprises and 0 for others), and *OwnCon* (the total shareholding ratio of the top ten shareholders of the firm). The detailed variable definitions are presented in Table A1. All regressions include firm and year fixed effects. The robust t-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Reports Attention and Professional Analysts Attention

	(1) RepAtt	(2) RepAtt	(3) BePro	(4) BePro
SupC5	0.4995***		−0.1808*	
	(2.66)		(−1.81)	
SupC3		0.5091***		−0.1777*
		(2.72)		(−1.76)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	12,444	12,444	9,393	9,393
Number of Firms	2,262	2,262	1,922	1,922
Adjusted R^2	0.65	0.65	0.11	0.11

Panel B: Star Analysts Attention Based on Tobit Measure

	(1) BeStar	(2) BeStar	(3) StarNum	(4) StarNum
SupC5	−0.1367***		−2.4638***	
	(−2.87)		(−4.14)	
SupC3		−0.1323***		−2.3930***
		(−2.77)		(−4.01)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	10,136	10,136	12,623	12,623
chi2	394.18	393.57	996.89	995.73

Table 11 reports the results of the tobit regression for *RepAtt* and *BePro*. *RepAtt* is significant and positively associated with supplier concentration at the 1% level. Conversely, the coefficients of *SupC*5 and *SupC*3 in Columns (3) and (4), respectively, are negative and significant at the 10% level. These results indicate that supplier concentration increases analyst attention from the perspective of research reports and decreases the proportion of expert analysts.

In contrast to this increased analyst attention, when we focus on professional analysts, we find that they pay less attention to firms with higher supplier concentration. Panel B of Table 11 shows that the coefficient of *BeStar* is negative and significant at the 1% level, similar to the results of *BePro*. To explore whether this reduction is due to a larger base or a decrease in the number of star analysts, we introduce another explanatory variable, namely, the logarithm of the star analyst scale (*StarNum*). Columns (3) and (4) show that the coefficients of *SupC*5 and *SupC*3, respectively, are negative and significant at the 1% level. This suggests that supplier concentration attracts additional analysts but results in a reduction in attention from star analysts. Firms with higher supplier concentration may have simpler businesses and may therefore be more attractive to average analysts. However, star analysts are likely to be cautious of the increased risk in the supply chain and thus avoid such firms.

6.2. Analyst concerns regarding supply chains

Our aim is to clarify that supplier concentration can improve analysts' focus on the supply chain. Although the result in the Guan et al. (2011) suggests that this is the case, they do not provide certain evidence. We use

Table 12
Analysts' Concerns about Supply. The table presents the impact of supplier concentration on the focus of analysts' attention for a sample of China-listed firms from 2008 to 2019. Tobit regression is used for the regression. The dependent variables are *Upstream* (a dummy variable of whether problems contain the keyword "upstream") and *RawMaterial* (a dummy variable of whether problems contain the keyword "raw material") in year t. The main explanatory variables are *SupC*5 and *SupC*3, which are the supplier concentrations calculated as the sum of the squared sales-based purchasing ratios of the top five and three suppliers, following Campello and Gao (2017) and Patatoukas (2012). The control variables include *Size* (the natural logarithm of total assets), *Lev* (total liabilities to total assets), *ROA* (net income over total assets), *Age* (the natural logarithm of the age of the firm), *MepsVol* (the volatility of *Meps*), *Loss* (a dummy variable that is 1 when net profit is negative and 0 otherwise), *SOE* (a dummy variable, 1 for state-owned enterprises and 0 for others), and *OwnCon* (the total shareholding ratio of the top ten shareholders of the firm). The detailed variable definitions are presented in Table A1. All regressions include firm and year fixed effects. The robust t-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1) Upstream	(2) Upstream	(3) Raw Material	(4) Raw Material
SupC5	0.1130***		0.0941*	
	(3.27)		(1.89)	
SupC3		0.1144***		0.0873*
		(3.20)		(1.69)
Size	0.0019	0.0019	0.0059**	0.0058**
	(1.03)	(1.01)	(2.22)	(2.20)
Lev	0.0120	0.0119	−0.0558***	−0.0561***
	(1.08)	(1.07)	(−3.54)	(−3.56)
ROA	0.1258***	0.1256***	0.1543***	0.1540***
	(3.37)	(3.36)	(3.04)	(3.03)
Age	−0.0008	−0.0008	0.0134*	0.0134*
	(−0.17)	(−0.17)	(1.92)	(1.92)
MepsVol	0.0148**	0.0148**	0.0235***	0.0235***
	(2.25)	(2.25)	(2.59)	(2.59)
Loss	0.0042	0.0042	−0.0005	−0.0005
	(0.48)	(0.49)	(−0.04)	(−0.04)
SOE	−0.0062	−0.0062	0.0063	0.0063
	(−1.42)	(−1.42)	(1.09)	(1.10)
OwnCon	0.0326***	0.0326***	−0.0143	−0.0143
	(2.66)	(2.66)	(−0.85)	(−0.85)
Observations	7,597	7,597	7,597	7,597
chi2	46.54	46.14	60.49	59.80

the analyst research record data in our database to further investigate this issue. We extract keywords from the questions asked by analysts when researching firms and use these to construct dummy variables for our study. We choose two targeted keywords, "Upstream" and "Raw Material," and assign a value of one to analyst questions containing these keywords; otherwise, the questions take a value of zero. Due to limited data, some observations are lost in this process.

Table 12 shows the results. Columns (1) and (2) present the results for the dummy variable of the keyword "Upstream." The coefficients of *SupC*5 and *SupC*3 are both positive and significant at the 1% level, indicating that an increase in supplier concentration improves analyst attention to the upstream of firms' supply chains. Similarly, Columns (3) and (4) report the results for the dummy variable of the keyword "Raw Material." In this case, the coefficients of the supplier concentration proxy variables are generally positive and significant at the 10% level. This suggests that improving supplier concentration can increase the attention that analyst pay to firms' sources of raw materials. When combined with our earlier results, it is clear that analysts are paying increasing attention to the supply chain itself, particularly at the supplier end, due to the increasing concentration of the supply chain. This confirms that supplier concentration increases the number of analysts following firms and encourages analysts to pay more attention to the supply chain.

7. Conclusion

Studies reveal that analysts can increase their forecast accuracy by keeping track of the disclosures of their major suppliers and customers (Guan et al., 2015; Luo and Nagarajan, 2015), and thereby communicate the correct signals to the capital markets. This study supports and extends this conclusion by exploring the specific influence of the supply chain structure on this effect. It complements research on the effects of supply chains on firms (Raman and Shahrur, 2008; Chu et al., 2019) and identifies new non-financial information that can affect analysts' forecast behavior.

This study examines the influence of supplier concentration on analyst forecasts using listed firms in the Chinese market from 2008 to 2019 as a sample. We find that higher supplier concentration leads to less divergence in analyst forecasts. Our results remain significant after controlling for omitted variable bias and reverse causality issues through IV regression and PSM. Furthermore, we conduct various robustness tests, including substituting proxy variables of supplier concentration and analyst forecast behavior and adding control variables to the modeling method. Our results remain robust and significant following these checks. We find that supplier concentration significantly influences analyst forecasts, particularly for firms with low transparency, high institutional ownership ratios and competitive industries. We further explore the channels through which supplier concentration can promote analyst forecasts and find that it attracts increasing attention from analysts, resulting in a reduction in analyst forecast dispersion. In addition, we analyze the composition of analysts following firms with high supplier concentration and find that they are typically not star analysts with strong expertise and experience, but average analysts. This is likely to occur because firms with higher supplier concentration have simpler businesses and present less difficulty for analysts to track their supply chains. Thus, firms with high supplier concentration find it easier to attract relatively inexperienced analysts.

The findings of this study illustrate that the supply chain relationship can have a significant impact on firms. From a policy perspective, the relevant regulatory agency should strengthen the requirements for supply chain information disclosure by listed firms to improve the information efficiency of the Chinese capital market.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix.

See Table A1.

Table A1
Variable Definitions.

Variable	Definitions
Dependent Variables	
FDISP1	The standard deviation of analyst forecast divided by the 12-month average of share price, following the method of Hope (2003a) and Johnson (2004)
FDISP2	The standard deviation of analyst forecast divided by share price of the year, following the method of Zhang (2006b)
FDISP3	The standard deviation of analyst forecast divided by the actual value, following the method of Papakroni (2013)
FERROR	The absolute value of the difference between the mean of analysts' forecast and the true value divided by the share price of the beginning of the year, following Brown and Kim (1991) and Lys and Soo (1995)
Explanatory Variables	
SupC5	The supplier concentration is calculated by the HHI method, and the specific calculation method is:$SupC5_{it} = \sum_{j=1}^{5}\left(\frac{Sales_{ijt}}{Sales_{it}}\right)^2$
SupC3	The supplier concentration is calculated by the HHI method, and the specific calculation method is:$SupC3_{it} = \sum_{j=1}^{3}\left(\frac{Sales_{ijt}}{Sales_{it}}\right)^2$
T5	Total purchasing share of the top five suppliers
Size	Natural logarithm of a firm's total assets
Lev	The ratio of a firm's total liabilities to total assets
ROA	Return on assets, which is the ratio of net profit to total assets
Age	Natural logarithm of the number of years since initial public offerings
MepsVol	A firm's earnings per share volatility, which is expressed as the standard deviation of the previous five periods
Loss	Dummy that equals 1 for the firm's net profit is negative and 0 otherwise
SOE	Dummy that equals 1 for the state-owned firm and 0 otherwise
OwnCon	The total shareholding ratio of the top ten shareholders of the firm
Horizon	The range of analysts' forecast, which is the natural logarithm of the median analysts' forecast time to the day the annual results are released
BM	Market-to-book ratio of assets
CF	The ratio of monetary funds held by a firm to total assets
FA	The ratio of fixed assets held by a firm to total assets
FFIN	Dummy equals 1 for the firm, which has a higher than the industry-year mean of Accrual and 0 otherwise. It's a measure of firm-level financial transparency measured by industry- and year-adjusted total scaled accruals (Bhattacharya, Daouk, and Welker, 2003; Dhaliwal et al., 2012). Scaled accruals (ACCRUAL) are computed as: $ACCRUAL = (\Delta CA - \Delta CL - \Delta CASH + \Delta STD - DEP + \Delta TP)/lag(TA)$, where ΔCA is the change of total current assets, ΔCL is the change of total current liabilities, $\Delta CASH$ is the change of cash held, ΔSTD is the change of the current portion of long-term debt included in total current liabilities, DEP is depreciation and amortization expense, ΔTP is the change of income taxes payable and $lag(TA)$ is total assets at the end of the previous year.
InstHolder	The ratio of Institutional shareholding
Other Variables	
HHI	Industry concentration is calculated using the Herfindahl index, following Hou and Robinson (2006). It is calculated by $HHI_{it} = \sum_{i=1}^{I}\left(s_{ij}\right)^2$, where s_{ij} is the market share of firm i in industry j.
Follow	Natural logarithm of the number of analysts or teams following the firm in the same year
SYN	Stock price synchronization calculated using R^2 statistic from the market model, following Roll (1988)
KV	The coefficient of the impact of trading volume on yield, following Kim and Verrecchia (2001). KV is calculated as: $Ln\left\|\frac{\Delta P_t}{\Delta P_{t-1}}\right\| = \alpha + \beta(Vol_t - Vol_0) + \mu_i$, where P is the closing price on day t, Vol_t is the number of shares traded on day t, Vol_0 is the annual average number of shares traded, $\beta * 1000000$ is KV
Accrual	The accrued profit used in calculating FFIN, see the definition method of FFIN
ES	Earning Smooth is the relationship between reported earnings and true earnings of a listed firm, calculated as: $\frac{std\left(Cash_{t-3,t}/BA_{t-3,t}\right)}{std\left(NI_{t-3,t}/BA_{t-3,t}\right)}$, where $std\left(Cash_{t-3,t}/BA_{t-3,t}\right)$ is the standard deviation of the ratio of the firm's net cash flow from operating activities between year $t-3$ and year t to the ratio of total assets at the beginning of the same year, the same thing in the denominator and NI is net profit (Bhattacharya, Daouk, and Welker, 2003).

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