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Do supplier analysts react to customers' data asset information disclosure?

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Abstract:

This study examines whether customers' data asset information disclosure improves suppliers' analysts forecast accuracy. Using data from Chinese firms between 2010 and 2024, this study uses text analysis to measure the degree of data asset information disclosure. The findings suggest that more customer data asset disclosure reduces analyst forecast errors for supplier firms, thereby improving analyst forecast accuracy for supplier firms. The results are robust to various endogeneity and robustness checks. The mechanism analysis shows that customer data asset disclosure improves forecast accuracy by enhancing information transparency and signaling customers' future performance. The effect is more pronounced in firms with more stable supply chain relationships, higher customer concentration, and when customers belong to high-tech industries. Overall, this study provides new empirical evidence that customers' data asset information has a significant spillover effect along the supply chain by offering analysts additional information to better understand supplier firms' performance and make more accurate forecasts.

Keywords: analyst forecasts; data asset information disclosure; supply chain; information spillover

JEL Classification: G30; M41

1. Introduction

In the digital era, firms collect and generate massive amounts of data through daily business activities or related transactions, gaining huge economic benefits through data production and data application (Veldkamp, 2023). Accordingly, data has emerged as a critical corporate asset (Kozjek et al., 2018). According to *The White Paper on Data Asset Management*

Practice (Version 4.0), data assets refer to the data resources owned or controlled by firms that have the potential to generate future economic benefits ("Data Assets"). From the perspective of resource-based theory, data assets, as a new type of intangible assets, serve as unique and valuable resources (Li et al., 2022). Existing studies confirm that data assets have become an important driver of firm value creation, improving operational efficiency, stimulating innovation, and reshaping strategic decision-making (Hannila et al., 2022; Hu et al., 2022; Zhang et al., 2025; Wei et al., 2025). As a result, external investors increasingly refer to the scale and application of firms' data assets when making value judgments and performance forecasts.

With the growing importance of data assets, data asset information becomes increasingly useful and valuable. Rajgopal and Venkatachalam (2011) argue that in a high-technology, intangible and information-intensive economy, disclosures related to intangible assets (e.g. data assets) become increasingly essential, whereas the usefulness of traditional financial information declines. In practice, firms increasingly disclose such information in their annual reports, highlighting the scale, application and development prospects of their data assets (Zhang et al., 2025; Wei et al., 2025). For example, Midea Group (Stock code: SZ.000333) disclosed in its annual report that, to better integrate online and offline data resources, it established a user-oriented operating platform based on users' data assets, bringing 5.5 billion yuan in revenue. Existing studies use textual analysis methods to measure the level of data asset disclosure and evidence the economic consequences of data asset information (Sun and Du, 2024). Specifically, prior research shows that greater data asset disclosure reduces idiosyncratic stock return volatility, improves nonprofessional investors' judgment, as well as improves bank lending acquisition (Li et al., 2022; Wei et al., 2025; Zhang et al., 2025). However, few studies examine the impact of data asset information disclosure along the supply chain. To fill this gap, this paper investigates whether and how supplier analysts take into consideration customer information when making forecasts.

Customers play a vital role in the supply chain since their purchase of goods and services significantly affects suppliers' financial policies and operating performance (Banerjee et al., 2008; Cohen and Li, 2020). Previous studies show that information disclosed by customers has a contagious effect on suppliers (Hertzel et al., 2008; Pandit et al., 2011; Li et al., 2021). For example, customer monthly sales announcements, bankruptcies, and customer stock prices influence the stock prices of supplier firms (Olsen and Dietrich, 1985; Hertzel et al., 2008; Pandit et al., 2011). Moreover, customer information also conveys signals about the operational status and future prospects of the supply chain, and provides useful implications and information to external stakeholders (Cohen and Frazzini, 2008; Johnstone et al., 2014; Guan et al., 2015; Luo and Nagarajan, 2015). In this study, we examine the customer information spillover effects from the perspective of analysts.

Analysts are important information intermediaries in capital markets. They generate earnings forecasts and make buy or sell recommendations by gathering, validating, and analyzing firms' disclosed information (Merkley, 2014). Accurate earnings forecasts provide valuable incremental information to investors and are crucial for market efficiency (Healy and Palepu, 2001). To improve forecast accuracy, analysts rely on a variety of information, including both financial and non-financial disclosures (Dhaliwal et al., 2012). Existing literature has primarily focused on the effects of macro-level information (Hugon et al., 2016), peer-industry information (Ramnath et al., 2008; Hilary and Shen, 2013), and firm-specific information (Dhaliwal et al., 2012; Beyhaghi et al., 2022; Chen et al., 2025). Besides, to improve forecast accuracy, analysts incorporate information from supply chain relationships. For example, Son et al. (2016) find that analysts do care about supply chain capabilities because of the close economic interdependence among supply chain partners. Guan et al. (2015) and Luo and Nagarajan (2015) further show that tracking information disclosed by suppliers and customers can improve analyst forecast accuracy and provide more informative signals to capital markets. Based on previous research, we investigate whether and how supplier analysts incorporate customer data asset information when making forecasts.

We propose that customer data asset information disclosure offers supplier analysts more bases for analysis, and ultimately improves the accuracy of their earnings forecasts. We examine this conjecture in the Chinese setting for two reasons. First, the Chinese government provides comprehensive support for firm data asset deployment and application. Data asset information disclosures in Chinese firms serve as a valuable model for data asset information provision in the digital era. Second, prior studies suggest that Chinese firms rely heavily on relationship-based transactions (Li et al., 2020). Therefore, the spillover effects of customer data asset information will be more significant and useful to analysts.

Using data from Chinese firms between 2010 and 2024, we collect publicly disclosed information on suppliers' top five customers and find that customer data asset disclosure significantly improves supplier analysts' forecast accuracy. Although we have controlled for firm fixed effects and year fixed effects in our main regression models, our results may still be subject to endogeneity problems. We use a Heckman two-stage approach, 2SLS analysis, and single-stage lag processing. Our findings remain robust to several tests designed to address endogeneity concerns.

Besides, we further investigate the mechanisms. First, we argue that customer data asset information disclosure expands the channels through which analysts can know firms, thereby alleviating information asymmetry and improving information transparency. Consistently, we find that customer data asset information increases customer information transparency measured by accrual-based earnings management. We also examine whether the customer data asset information disclosure complements the financial reporting information of suppliers, using supplier accrual-based earnings management and suppliers' voluntary performance forecast disclosure as proxies. The results suggest that customer data asset information disclosure serves as an important supplementary information source for analysts.

Second, we argue that a higher level of customer data asset information disclosure is associated with improved signaling for customer performance, which is informative about suppliers' future earnings. Consistently, we find that customer data asset information disclosure signals better firm performance as reflected in higher supplier firm value. Furthermore, we examine the effect of customer data asset information on customer firm value, captured by customer business risks and firm performance.

Overall, these results support our conjecture that customer data asset information has a significant spillover effect along the supply chain, providing analysts with additional information to better understand supplier performance and produce more accurate earnings forecasts. And this relationship is more pronounced when supplier-customer relationships are more stable, when customer concentration is higher, and when customers are high-tech firms. Finally, we find that customer data asset disclosure also reduces supplier analysts' forecast dispersion.

This article contributes to the literature as follows. Firstly, we provide new empirical evidence on data assets and enrich the data asset disclosure literature. Prior studies show that data asset information can improve investors' judgment and enhance market efficiency (Li et al., 2022; Sun and Du, 2024; Wei et al., 2025). Based on this, we investigate the economic consequences of data asset information disclosure from a supply chain perspective. Specifically, we find that customer data asset disclosure enhances information transparency of customer firms and is informative about suppliers' future earnings, thereby increasing the accuracy of analysts' forecasts for suppliers.

Secondly, this study contributes to the literature on the factors influencing analysts' forecast accuracy by highlighting the role of customer data asset information. Whereas previous studies primarily focus on firms' own disclosure practices (Dhaliwal et al., 2012; Muslu et al., 2019; Demmer et al., 2019; Beyhaghi et al., 2022), our study extends the corporate boundaries and shows that analysts also incorporate customers' data asset information into their earnings forecasts. Our findings suggest that customer data asset disclosure improves supplier analysts' forecast accuracy and thus offers a new perspective on the factors that influence analysts' forecasts.

Thirdly, this study contributes to the literature on supply chain information spillover. Existing studies have examined how firms' information disclosure affects their supply chain partners, particularly suppliers (e.g., Hertzel et al., 2008; Pandit et al., 2011; Patatoukas, 2012). As data asset information becomes more essential in the digital economy, we extend this literature by exploring whether analysts use customer firms' data asset information when forecasting supplier earnings. We reveal the economic outcomes of supply chain information spillovers resulting from data asset information, and we confirm the positive impact of such information on supply chain synergy by considering analysts' forecasts.

The rest of this paper is organized as follows. Section 2 reviews the related literature and develops hypotheses. Section 3 describes the sample and presents the research design. Section 4 reports the empirical results and conducts further analyses. Section 5 concludes, provides managerial implications, and discusses the limitations of the research and possible directions for future research.

2. Literature review and hypothesis development

2.1 Data asset information disclosure

Current research has primarily focused on the effects of digital transformation and big data deployment on firms, such as innovation, operating performance, decision-making effectiveness, as well as corporate social and environmental performance (Dubey et al., 2019; Ghasemaghaei and Calic, 2020; Awan et al., 2021; Li et al., 2022; Beraja et al., 2023). However, few studies have directly examined the role of data assets. With digital transformation, enterprises accumulate, manage, and utilize data and convert data into valuable data assets (Hu et al., 2022; Ma et al., 2025). Resource-based theory suggests that data assets, as a new form of intangible assets, are unique and valuable firm resources and have become important drivers of future growth and innovation for firms (Li et al., 2022;

Sun and Du, 2024). According to the definition in the *White Paper on Data Asset Management Practices (Version 4.0)* of China Academy of Information and Communications Technology, data assets refer to data resources owned or controlled by firms that have the potential to generate future economic benefits (Wei et al., 2025). It is clear that data have become a type of critical firm asset (Kozjek et al., 2018). Existing studies examine the value qualities and evaluation of data assets extensively (Wang and Zhao, 2020; Birch et al., 2021; Birch, 2023; Veldkamp, 2023), and document the positive effects on firm decision-making, operating efficiency, green innovation, and sustainable development (Brynjolfsson et al., 2016; Farboodi et al., 2019; Xu et al., 2022; Hu et al., 2022; Li et al. 2024; Chen, 2024; Zhang et al., 2025). From a supply chain perspective, some research suggests that data assets facilitate information integration across the supply chain, and thereby enhance firm competitiveness (Gunasekaran et al., 2017; Wang et al., 2018).

As data assets have become critical intangible assets, their value creation has been an important measure during firm transformation, and investors are paying growing attention to firms' data asset applications (Sun and Du, 2024; Li et al., 2022). Besides, because traditional financial statements are less useful in the digital economy (Rajgopal and Venkatachalam, 2011; Wei et al., 2025), textual disclosure of intangible asset information in annual reports, such as data asset information disclosure, has become more important (Ritter and Wells, 2006). As a result, data asset information provides valuable incremental information (Shi et al., 2025; Luo, 2025). Currently, the disclosure of data asset information is still voluntary, and firms lack standardized methods for quantifying data assets (Wei et al., 2025). Consequently, firms generally disclose textual information about data assets in their annual reports (Qian et al., 2025). According to current practice and research, firms usually demonstrate information regarding firm data size, data management, and data application and convey the development prospects of their data assets (Li et al., 2024; Zhang et al., 2025; Xiao et al., 2025). Firms also have incentives to disclose data asset information to signal their innovative capacity and enhance transparency (Xiao et al., 2025; Feng et al., 2025). Prior research evidences that data asset information effectively conveys firms' unique value to capital markets and positively affects nonfinancial investor judgment, market efficiency, as well as access to bank lending (Li et al., 2022; Sun and Du, 2024; Wei et al., 2025; Qian et al., 2025; Luo, 2025).

2.2 Analysts' reaction to supply chain information

In supply chains, suppliers and customers are involved in close financial credit relationships and goods transactions. Previous research shows that shocks affecting one firm in the supply chain can influence the performance of its linked partners (Hertzel et al., 2008; Pandit et al., 2011; Patatoukas, 2012). As an important and ongoing source of revenue, customers are often regarded as the most direct and influential stakeholders for suppliers (Arora and Alam, 2005). Olsen and Dietrich (1985) confirmed that information complementarities exist between suppliers and customers along a supply chain network. Consistent with this view, prior studies find that customer characteristics affect suppliers' financial decision-making, cost of capital, management earnings forecast, sales forecasts, and tax avoidance (Dhaliwal et al., 2011; Itzkowitz, 2013; Cen et al., 2017; Crawford et al., 2020; Munir et al., 2020; Baghersad and Zobel, 2021). Moreover, customer information, such as earnings announcements, risk information as well as bankruptcy announcement, has significant impacts on suppliers' stock prices (Olsen and Dietrich,1985; Pandit et al., 2011; Li et al., 2021), and investment efficiency (Chiu et al., 2019; Chen et al., 2019). Overall, these studies suggest that customer information is useful and relevant to suppliers.

Information spillover effects suggest that information disclosed by listed firms in capital markets has a material effect on other economic entities (Chen et al., 2013; Li et al., 2024). Consistently, customer information can provide useful implications and information to external stakeholders, including auditors, investors, and analysts (Cohen and Frazzini, 2008; Johnstone et al., 2014). Specifically, Cheng and Eshleman (2014) show that investors trade on the earnings news of supply-chain partners. Madsen (2017) finds significant increases in customer information acquisition before suppliers' earnings announcement dates, suggesting supplier investors pay greater attention to customer firms during these periods. In this study, we investigate the customer information spillover effects from the perspective of financial analysts.

Analysts serve as important information intermediaries between firms and investors, playing a significant role in promoting capital market efficiency. Their primary goal is to predict information accurately (Hong and Kubik, 2003), and higher forecast accuracy enhances their reputation (Luo and Nagarajan, 2015). Previous studies find that firms with more accurate analyst forecasts tend to exhibit higher trading volumes, greater liquidity, as well as lower transaction costs (Alford and Berger, 1999; Lang and Maffett, 2011; Lang et al., 2012). To improve forecast quality and facilitate firm investment efficiency, analysts collect and interpret a wide range of relevant information. Existing studies find that analyst forecast accuracy is positively associated with firms' voluntary disclosure, including both financial information (Hope, 2003) and non-financial information (Dhaliwal et al., 2012; Muslu et al., 2019; Tsang et al., 2022; Beyhaghi et al., 2022), ESG perfomance (Chen et al., 2025; Cheng et al., 2025), firm size (Lang and Lundholm, 1996), earnings variability, and profitability (Kross et al., 1990).

Based on previous studies, we further investigate whether and how supplier analysts incorporate customer data asset information into their forecasts. Consistently, Chang et al. (2009) and Son et al. (2016) find that analysts pay attention to supply chain capabilities and use both customer and supplier earnings information when making forecast revisions. Guan et al. (2015) suggest that supplier–customer analysts benefit from the informational complementarities along the supply chain and improve their forecast accuracy. Luo and Nagarajan (2015) further show that analysts are able to exploit such complementarities to produce more accurate and less biased earnings forecasts. Accordingly, we expect that supplier analysts respond to customer data asset information.

2.3 Hypothesis development

We propose that customer data asset information disclosure provides supplier analysts with more bases for analysis, and ultimately improves supplier analysts' forecast accuracy. There are two reasons: firstly, customer data asset information disclosure expands the channels through which analysts obtain firm-relevant information, thereby reducing information asymmetry and improving information transparency. Specifically, data asset disclosure directly increases the amount of publicly available information by revealing details about data leverage, digital initiatives, and data asset applications, which could be difficult to observe or acquire (Hu et al., 2022; Zhang et al., 2025; Luo, 2025). This richer information environment enhances analysts' ability to make more accurate forecasts based on publicly disclosed information.

In addition, disclosure about firms' data assets supplements information on traditional "hard assets" (Sun and Du, 2024), allowing analysts to capture incremental information about off-balance sheet assets (Wei et al., 2025) and to integrate market data with firms' financial data in a more comprehensive way. Furthermore, customer data asset information disclosure conveys forward-looking information that helps analysts assess suppliers' future value potential (Ma et al., 2025). In particular, data asset information reflects firms' technological infrastructure, R&D investment, and innovation practices, thereby signaling firms' future growth potential (Xiao et al., 2025; Qian et al., 2025). Taken together, we argue that greater customer-specific disclosure helps analysts access more supply chain risk and customer capability from a multi-dimensional perspective, thereby supplementing and validating suppliers' own financial reporting information (Guan et al., 2015; Luo and Nagarajan, 2015). Moreover, the information that analysts obtained from customers provides useful indicators for suppliers because firms along the supply chain are affected by some common factors such as technological shocks, price, supply, or demand (Guan et al., 2015). Overall, customer data asset information disclosure alleviates information asymmetry and enhances transparency, enabling analysts to produce more accurate earnings forecasts for suppliers.

Secondly, higher levels of customer disclosure are associated with improved signaling for customer firm performance, which is informative about suppliers' future earnings. With the rapid development of big data technologies and digital transformation, the value creation of data assets is gradually becoming apparent, and data assets represent firms' entitlement to digital technologies and data application. (Li et al., 2022; Ma et al., 2025). Firms often disclose their data asset management and utilization capabilities to demonstrate their digital practice and competitiveness (Luo, 2025; Feng et al., 2025). As a result, data asset disclosure becomes an important indicator of an enterprise's operational ability and development potential (Wei et al., 2025). When customers disclose more data asset information, external stakeholders are better able to understand how firms leverage data assets for innovation and product development, as well as the forms and value-generation mechanisms related to their data assets (Hu et al., 2022; Sun and Du, 2024). Such disclosure can ease financing constraints and improve bank lending acquisition (Hasseldine et al., 2005; Qian et al., 2025), thereby improving customer performance. Consequently, a higher level of data asset disclosure is likely to be associated with better customer operating performance and earnings growth.

In terms of supply chain spillover effects, suppliers are highly sensitive to the operations and activities of their customers (Guan et al., 2015; Li et al., 2024). When customers experience strong earnings growth, their demand for supplier products is likely to increase, therefore increasing the supplier's revenue and earnings (Cho et al., 2020). Guan et al. (2015) suggest that because of close economic interdependence, customer performance is related to its supplier firm value, and value-relevant information about customers is also value-relevant for supplier firm value. This is consistent with the view of Luo and Nagarajan (2015) that when analysts are better informed about customers' growth opportunities, they are better able to understand the suppliers' profit drivers and predict supplier earnings. Accordingly, we expect that greater customer data asset information disclosure enables analysts to produce more accurate forecasts for supplier firms.

Based on the above analysis, this paper proposes the following hypothesis: The disclosure of customer data asset information can improve supplier analysts' forecast accuracy.

3. Sample selection and model specification

3.1 Sample selection

We test our hypothesis using data of Chinese listed firms from 2010 to 2024. Financial data are obtained from the CSMAR database, while annual reports are collected from the official websites of the Shenzhen and Shanghai Stock Exchanges. We obtain data on the top five suppliers or customers of Chinese-listed companies from the CSMAR database. According to the China Securities Regulatory Commission (CSRC), customer information disclosure belongs to voluntary disclosure (Wang et al., 2023). We constructed a dataset that documented supplier-customer-year information. For instance, in a certain year (t), a supplier (i) may have multiple customers (j_1, j_2), and we then created the observations i- j_1-t and i- j_2-t. Following Sun et al. (2023), we retain cases where both suppliers and customers are disclosed and listed companies. We further exclude missing variables, observations of financial firms, firms marked ST or ST*, and insolvent firms. Our final sample consists of 1185 unique supplier-customer-year pairs. The sample selection process is reported in Table 1. The small sample size is mainly driven by the following reasons: (1) information on customers' identity is missing in the database, or (2) the customer is not a publicly listed firm (Wang et al., 2023; Sun et al., 2023). Our sample size is comparable to those in customer-supplier relationship research based on similar settings in China (e.g., Peng and Wang, 2018; Luo and Yu, 2019). All continuous variables are winsorized at the 1st and 99th percentiles.

Table 2 presents the sample distribution by customer rank. Overall, the distribution of observations across the top five customer ranks is relatively balanced, indicating that the sample is reasonably distributed. Moreover, the number of observations declines slightly as customer rank decreases from first to fifth. The average sales ratio falls from 0.17 for the largest customer to 0.03 for the fifth-largest customer, which is consistent with the economic importance of major customers in supplier disclosure.

Table 1. Sample Selection Process

	Number of Observations
All the observations for listed firms in China over the period 2010–2024	157331
Delete:	
Observations that do not disclose names of customers	101750
Observations for unlisted customers	52330
Observations from ST, PT and financial industry (customers)	1023
Observations from ST, PT and financial industry (suppliers)	350
Observations with information for main variables	693
Final Sample	**1185**

Source: authors' processing

Table 2. Sample Distribution by Customer Rank

Rank	Number of observations	Average sales ratio
1	244	0.17
2	245	0.076
3	233	0.05
4	232	0.039
5	231	0.03
Total	1185	0.073

Source: authors' processing

3.2 Model specification

To test the main hypothesis, we construct the following regression model:

$$FERROR_{i,t} = \beta_0 + \beta_1 CusDA_{i,j,t} + Controls + f_{firm} + f_{Year} + \varepsilon_{i,j,t}$$

where *i* refers to supplier, *j* is customer, and year *t*. f_{firm} and f_{Year} denote firm and year fixed effects. The dependent variable $FERROR_{i,t}$ denotes the analyst earnings forecast accuracy for supplier. The key variable of interest is the indicator variable, $CusDA_{i,j,t}$, representing the extent of data asset information disclosure by customer.

Specifically, this study refers to the measurement method of Jia and Wu (2023), and adopts the company-level analyst earnings forecast error. The specific model is as follows:

$$FERROR_{i,t} = \frac{|Ave\_FEPS_{i,t} - MEPS_{i,t}|}{|BeginningPrice_{i,t}|}$$

where $FERROR_{i,t}$ is computed as the absolute difference between the actual EPS and the forecasts, scaled by the stock price at the beginning of the year. $FEPS_{i,t}$ is the analyst's forecast earnings per share of supplier. And $Ave\ FEPS_{i,t}$ is the mean of all analysts' forecast. $MEPS_{i,t}$ denotes the actual earnings per share of supplier. $Beginprice_{i,t}$ denotes the share price of supplier *i* at the beginning of year *t*. *FERROR* is an inverse measure of analyst forecast accuracy, suggesting that a larger value for this variable means that analysts are more inaccurate in their opinions.

Currently, the accurate recognition, measurement, and disclosure of data assets remain at an exploratory stage. Firms primarily disclose data asset information within annual reports. Accordingly, a text-based measure is a reasonable way to capture firms' disclosure of data asset holdings, applications, and related activities. Following Hu et al. (2022) and Sun and Du (2024), this study attempts to measure the data asset information disclosure level using text analysis methods. However, this may suffer from some potential limitations, such as using inaccurate seed words and the lack of objective textual support from relevant policy documents and research reports. Meanwhile, subjective judgments may also be involved, resulting in large deviations between the word sets and the actual situation. To address these concerns and ensure the vocabulary can effectively capture data-asset-related information, we review the relevant vocabulary descriptions in the policies related to data assets and refer to previous studies (Sun and Du, 2024; Wei et al., 2025). We then use texts of laws and regulations related to data assets as the corpus. As a result, the term "data asset" is selected as the seed word. Further, this paper employs the Word2Vec neural network model to train on a vast corpus. Specifically, Word2Vec simplifies the processing of text content into vector operations in vector space, and the similarity in vector space is used to measure the semantic similarity of text (Su et al., 2014; Hu et al., 2019). The top 10 words with the highest similarity are retained to ensure the accuracy of the measurement. Detailed keywords are shown in Appendix 1, and Appendix 2 presents several examples of original data asset disclosures from annual reports.

This study measures data assets at the level by setting up the keyword dictionary described above. The calculation is shown as the following equation:

$$CusDA_{i,j,t} = \frac{\sum Fre_{j,t}}{TotalFre_{j,t}} \times 100$$

where $CusDA_{i,j,t}$ is the data asset information disclosure frequency variable, $\sum Fre_{j,t}$ is the data asset related key word frequency in the annual report of customer. $TotalFre_{j,t}$ is the total word frequency in the annual report of the customer.

We include control variables related to analyst forecasts and customer firms. We first include the characteristics of the supplier including firm size (*Size*), leverage ratio (*Lev*), return on assets (*ROA*), star analyst coverage (*StarAnal*), intangible asset size (*Intan*), institutional investor ownership (*INST*), the ownership of largest shareholder (*Top1*), the proportion of executives with an IT background (*IT*), and firm's digitalization level (*Digital*). We further control for customer characteristics, including customer intangible asset size (*CusIntan*), the proportion of executives with an IT background of customer firms (*CusIT*), as well as customer's digital transformation level (*CusDigital*). Besides, we also consider the impact of supply chain, such as sales ratio (*Custincrt*), and supply chain concentration (*SC*). The detailed definitions of the main variables are presented in Appendix 3.

4. Empirical Analysis

4.1 Descriptive Statistics

Table 3 Panel A presents the descriptive statistics for the main variables. The mean value of *FERROR* is 0.0345, with a maximum of 0.239 and a minimum of 0.0001. This indicates the analyst's forecast accuracy varies widely among different firms. The mean value of *CusDA* is 0.0036, with a maximum of 0.0453 and a minimum of 0, indicating that the overall level of data asset information disclosure is not high and firms usually take a little space for data asset disclosure when they provide the information.

Panel B of Table 3 reports the yearly distribution of data asset information disclosure and shows an overall increasing pattern over the sample period. The mean value of *CusDA* increases from 0.00047 in 2010 to 0.016 in 2024, and the median of *CusDA* changes from 0 to 0.0164. Specifically, from 2010 to 2013, data asset information disclosure levels were low, with mean values close to 0 and median values equal to 0. From 2014 to 2016, the mean value of *CusDA* increased from 0.003 to 0.0049, but the median of *CusDA* remained 0, suggesting that some firms had begun to recognize the importance of data assets and disclose relevant information in their annual reports. This pattern is broadly aligned with the policy and industrial environment in China. In 2014, "Big Data" was incorporated into the Chinese Government Work Report for the first time. Since then, big data has attracted increasing attention, creating a favorable environment for firms to recognize, manage, and disclose data-related assets (Wang et al., 2024). From 2017 to 2024, both the mean and median were positive and showed an overall upward trend, rising from 0.005 and 0.001 in 2017 to 0.016 and 0.0164 in 2024, respectively. The results suggest that most firms had come to recognize the importance of data assets and a growing number of firms choose to disclose data asset information.

Further, we divide *CusDA* into two groups based on whether customers disclose data asset information. Panel C of Table 3 shows the sample distribution and summary statistics. The sample contains 754 firm-year observations with no customer data asset disclosure, suggesting that there is no data asset disclosure in most firms. 431 observations disclose data asset information in their annual reports. The mean value of *CusDA* is 0.01, and the median is 0.005 in the disclosing group (*CusDA>0*), indicating that the overall level of data asset disclosure still remains relatively low.

Table 3. Descriptive Statistics

Panel A: Descriptive Statistics of the Main Variables

Variable	N	Mean	SD	Min	P25	Median	P75	Max
FERROR	1,185	0.0345	0.0442	0.0001	0.0066	0.02	0.0432	0.239
CusDA	1,185	0.0036	0.0079	0	0	0	0.003	0.0453
Size	1,185	22.22	1.277	19.89	21.25	22.07	23.10	25.27
Lev	1,185	0.412	0.205	0.0401	0.251	0.414	0.556	0.887
ROA	1,185	0.0424	0.0573	−0.196	0.0154	0.0424	0.0712	0.185
StarAnal	1,185	0.723	0.781	0	0	0.693	1.386	2.303
Intan	1,185	18.58	1.784	13.51	17.62	18.68	19.69	22.84
INST	1,185	0.470	0.251	0.008	0.257	0.491	0.676	0.902
Top1	1,185	0.373	0.152	0.104	0.251	0.352	0.481	0.716
IT	1,185	0.0588	0.164	0	0	0	0	1
Digital	1,185	1.091	1.330	0	0	0.693	1.946	4.92
CusIntan	1,185	20.47	2.088	15.94	19.11	20.29	21.87	25.18
CusIT	1,185	0.0680	0.154	0	0	0	0.0588	0.8
CusDigital	1,185	1.273	1.323	0	0	1.099	2.197	4.489
Custincrt	1,185	0.073	0.0934	0.0042	0.0247	0.0445	0.0787	0.61
SC	1,185	0.306	0.175	0.0267	0.167	0.284	0.411	0.781

Panel B: Distribution of Data Asset Information Disclosure: types by year

Year	N	Mean	SD	Min	Median	Max
2010	120	0.00047	0.0017	0	0	0.011
2011	139	0.00025	0.0015	0	0	0.003
2012	150	0.00079	0.0035	0	0	0.023
2013	129	0.0015	0.0043	0	0	0.0231
2014	59	0.003	0.008	0	0	0.045
2015	64	0.003	0.006	0	0	0.03
2016	65	0.0049	0.01	0	0	0.045
2017	57	0.005	0.01	0	0.001	0.0452
2018	60	0.005	0.162	0	0.0014	0.0452
2019	57	0.005	0.008	0	0.0018	0.0452
2020	50	0.004	0.006	0	0.0019	0.031
2021	56	0.005	0.007	0	0.0029	0.0453
2022	60	0.007	0.012	0	0.0019	0.0453
2023	63	0.006	0.009	0	0.0028	0.0453
2024	56	0.016	0.012	0	0.0164	0.0453

Panel C: Customer-year observation with disclosed data assets information

Whether customers disclose data assets information	N	Mean	Median	SD
Customers do not disclose data assets information (*DA = 0*)	754	0	0	0
Customers disclose data assets information (*DA > 0*)	431	0.01	0.005	0.01
Total	**1185**	**0.0036**	**0**	**0.0079**

Notes: Detailed information on the variable construction of forecast accuracy and data assets information disclosure is provided in Appendix 1.

Source: authors' processing

4.2 Baseline Regression

Table 4 presents regression results for the effect of customer data asset disclosure (*CusDA*) on supplier forecast error (*FERROR*). The coefficient on *CusDA* is -0.854 and statistically significant at the 1% level (t = 2.63). This finding supports our main hypothesis, indicating that customer data assets disclosure significantly reduces supplier analysts' forecast error, thereby enhancing analyst forecast accuracy for supplier firms. Consistent with existing studies that analysts may be able to produce superior earnings forecasts by using supply chain information (Luo and Nagarajan, 2015; Guan et al., 2015). In terms of economic significance, a one standard deviation increase in *CusDA* translates into a decrease of 0.0067 (−0.854×0.0079) in the coefficient on *FERROR*. This effect accounts for approximately 19.6% of the sample mean of *FERROR* and 15.3% of its standard deviation.

In addition, control variables also show statistical significance in Table 4. Specifically, firm size (*Size*) has a positive and significant coefficient (0.021, $p<0.01$), suggesting that larger firms may have more complex operational structures and information environments, leading to higher forecast errors by analysts. Return on assets (*ROA*), star analyst coverage (*StarAnal*), and the firm's digitalization level (*Digital*) are significantly negatively associated with *FERROR*, consistent with the expectation that firms with better profitability and more star analysts' coverage have better operational performance, thus lowering forecast errors. Leverage (*Lev*) shows a negative and significant relationship with *FERROR* (−0.07, $p<0.01$), which may be because highly leveraged firms face strict monitoring. For customers, customer intangible asset size (*CusIntan*) and customer digitalization level (*CusDigital*) have positive coefficients, which may be due to the increased complexity of the supply chain information environment when customers have higher levels of intangible assets or digitalization.

Table 4. Baseline Regression

VARIABLE	*FERROR*
CusDA	**−0.854***** **(−2.63)**
Size	0.021*** (2.73)
ROA	−0.677*** (−15.1)
Lev	−0.07*** (−3.82)
StarAnal	−0.01*** (−3.98)
Intan	0.002 (0.85)
INST	−0.002 (−0.12)
TOP1	0.029 (0.92)
IT	−0.003 (−0.17)
Digital	−0.008*** (−3.84)
CusIntan	0.008** (2.57)
CusIT	−0.042** (−2.44)
CusDigital	0.006** (2.41)
SC	0.030* (1.8)
Custincrt	0.01 (0.25)
Constant	−0.566*** (−3.6)
Year and Firm Fixed Effect	Yes
Observations	1185
R-squared	0.505

Notes: This table reports the results of the main regression. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Source: authors' calculations

4.3 Robustness Test

To ensure the robustness of our findings, this section performs robustness tests including the replacement of variable measurement and exclusion of specific samples. Firstly, we use the logarithm value of the frequency of words related to data assets in the annual reports as an alternative measurement (*CusDA2*). The results are reported in column (1) of Table 5, which shows that the baseline results of this paper are robust ($\beta = -0.0054$, $t = -1.78$). Next, the dependent variable is recalculated by using the absolute value of the difference between the mean of analysts' forecasts and the true value divided by the share price at the end of the year. The specific model is shown in Appendix 3, and column (2) of Table 5 reports regression results suggesting that the baseline results of this paper are robust ($\beta = -0.695$, $t = -1.87$). These results suggest that the negative relationship between customer data asset disclosure and supplier forecast error still holds after altering the measurement method of the independent variables and dependent variables.

Additionally, to reduce the omitted variable bias, we include control variables about customer executives and CEO traits, as customer CEOs may have an impact on data asset disclosure. In this test, we include the shareholding ratio of the CEO (*CEOshares*), CEO duality (*Dual*), the average age of executives (*Age*), the proportion of female executives (*Female*), and the proportion of executives with overseas backgrounds (*Overseaback*). Table 5 Panel B shows that the relationship between customer data assets information disclosure and supplier forecast error remains significant after we control for customer managerial characteristics.

Lastly, we exclude the sample period 2020-2022 to eliminate the macroeconomic shock of the pandemic. The COVID-19 outbreak may have had a negative impact on firms' production, business conditions, as well as supply chain operations. Table 5 Panel C reports the results. The coefficient of *CusDA* is -0.788 is statistically significant at the 5% level, confirming the robustness of our main findings.

Table 5. Robustness Test

Panel A: Robustness test: Alternative measurements

VARIABLES	*FERROR*	*FERROR2*
	(1)	**(2)**
CusDA2	**−0.0054*** **(−1.78)**	
CusDA		**−0.695*** **(−1.87)**
Controls	Yes	Yes
Constant	Included	Included
Year and Firm Fixed Effect	Yes	Yes
Observations	1185	1185
R-squared	0.501	0.563

Panel B: Robustness test: Adding control variables related to customer executives and CEO traits

VARIABLES	*FERROR*
CusDA	**−0.720**** **(−1.98)**
CEOshares	−0.407 (−1.38)
Dual	0.004 (0.50)
Overseaback	−0.028 (−1.25)
Age	0.003* (1.76)
Female	−0.017 (−0.38)
Controls	Yes
Constant	Included
Year and Firm Fixed Effect	Yes
Observations	1,068
R-squared	0.506

Panel C: Robustness test: Alternative samples (excluding Covid-19)

VARIABLES	*FERROR*
CusDA	**−0.788**** **(−2.30)**
Controls	Yes
Constant	Yes
Year and Firm Fixed Effect	Included
Observations	1019
R-squared	0.429

Notes: This table reports the results of robustness results. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Source: authors' calculations

4.4 Endogeneity Concerns

Table 6 shows the results of endogeneity tests. Firstly, a potential concern is that our findings may be driven by shared firm characteristics rather than the actual economic linkage between firms. To address this issue, we conduct a placebo test using propensity score matching (PSM). Specifically, for each actual firm pair, we identify matched firms with similar observable characteristics but without a real economic relationship. The variables used for constructing the matched firms for suppliers include firm size (*Size*), return on assets (*ROA*), leverage ratio (*Lev*), institutional investor ownership (*INST*), intangible asset size (*Intan*), and the firm's digitalization level (*Digital*). The balancing test results are reported in Panel A, suggesting that after matching, there is no statistically significant difference. Similarly, we incorporate customer firm size (*CusSize*), return on assets (*CusROA*), leverage ratio (*CusLev*), customer cash flow (CusCashflow), intangible asset size (CusIntan), and customer digitalization level (*CusDigital*) for constructing the matched firms for customers. The balancing test results are reported in Panel B. In Panel C Column (1), we repeat our main analysis using the matched sample of firms. Specifically, the coefficient on CusDA is -0.059, with a t-statistic of -0.28, indicating that it is insignificant. This suggests that the spillover effect of customer data asset information disclosure is not driven by other confounding factors, but by the underlying economic link between customers and suppliers.

Currently, the disclosure of customer names remains voluntary, which introduces potential sample self-selection bias in this study. To deal with this issue, we use a Heckman two-stage model. In the first stage, we estimate a probit model using *CusDummy* as the dependent variable, together with all control variables. In the second stage, we include the Inverse Mills Ratio (IMR) obtained from the first-stage regression as an additional control variable in the regression model. After introducing IMR in the baseline regression, the coefficient on *CusDA* remains significantly negative (coefficient = −0.654, t = −1.87), which is consistent with our baseline findings. These results are shown in Panel C Column (2), suggesting that the relationship between customer data asset disclosure and supplier analysts' forecast error remains robust after accounting for potential self-selection.

However, although we control for supplier-level and customer-level characteristics, the endogeneity concerns may still be present because of sample selection bias and potential reverse causality. To deal with the potential issues, we perform 2SLS analysis. Specifically, we use the average data asset information disclosure frequency of the same year-industry excluding the company's own data (*CUSID*), and the average data assets information disclosure frequency of the same year-province excluding the company's own data (*CUSPRV*) as instruments. We expect that firms in the same industry face similar product market competition, disclosure norms, and regulatory pressures. Similarly, firms located in the same province have similar institutional environments, digital infrastructure, and regional disclosure incentives. Therefore, customer data asset disclosure could be influenced by peer effects and the surrounding disclosure environment. Moreover, *CUSID* and *CUSPRV* are exogenous to analysts' forecast errors of suppliers since they do not directly capture customer characteristics or the supplier information environment. Empirically, the weak instrument test (first-stage F-statistic = 293.61>10) and overidentification test (p-value = 0.2) support the validity of our instruments. Columns (3) and (4) in Panel C report results. In Column (3) of Panel C, the coefficient on *CUSID* is 0.43 (t = 9.73), and the coefficient on *CUSPRV* is 0.7 (t = 15.54), which is consistent with our expectation. The coefficient of *CusDA* is significantly negative in the second-stage regression reported in Column (4), Panel C, indicating that our main results are robust to potential endogeneity.

Lastly, to alleviate the potential reverse causality between customer data asset disclosure (*CusDA*) and supplier forecast error (*FERROR*), we use a single-stage lag processing. Specifically, it is possible that suppliers' forecast errors may inversely affect customers' willingness or level of data asset disclosure. To address this concern, we replace *CusDA* with its lagged value (*L.DA*). The results, reported in Panel C column (5), show that the coefficient of *L.DA* remains significantly negative. Overall, our results hold for endogeneity issues.

Table 6. Endogeneity Test

Panel A: PSM Balance test for suppliers and matched firms

	Mean			Difference of treated and Control	
VARIABLES	**Treated**	**Control**	**%bias**	**T-value**	**P-value**
Size	22.233	22.331	−7.6	−0.13	0.893
ROA	0.0422	0.0433	−1.9	−0.04	0.972
Lev	0.412	0.406	2.8	0.05	0.960
INST	0.47	0.477	−3.1	−0.05	0.957
Intan	18.592	18.642	−2.9	−0.05	0.960
Digital	1.1	1.12	−2.0	−0.04	0.971

Panel B: PSM Balance test for customers and matched firms

	Mean			Difference of treated and Control	
VARIABLES	**Treated**	**Control**	**%bias**	**T-value**	**P-value**
CusSize	24.12	23.94	9.4	0.36	0.718
CusROA	0.044	0.048	−7.1	−0.26	0.795
CusLev	0.574	0.569	3.3	0.12	0.901
CusCashflow	0.057	0.058	−0.5	−0.02	0.985
CusIntan	20.368	20.331	1.7	0.07	0.946
CusDigital	1.28	1.44	−11	−0.43	0.666

Panel C: Endogeneity tests results

	(1)	(2)	(3)	(4)	(5)
	Second Stage				
VARIABLES	***FERROR***	***FERROR***	***CusDA***	***FERROR***	***FERROR***
CusDA	**−0.059** **(−0.28)**	**−0.654*** **(−1.87)**		**−1.110***** **(−4.09)**	
IMR		**−0.024** **(−1.51)**			
CUSID			**0.43***** **(9.73)**		
CUSPRV			**0.7***** **(15.54)**		
L.DA					**−1.44***** **(−3.98)**
Controls	Yes	Yes	Yes	Yes	Yes
Constant	Included	Included	Included	Included	Included
Year and Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	707	1185	948	948	1003
R-squared	0.831	0.508	0.9	0.854	0.497

Notes: This table presents the results of endogeneity tests in our study. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Source: authors' calculations

4.5 Further Analysis

4.5.1 Does customer data asset disclosure provide more information?

In this section, we validate our first channel: whether customer data asset information disclosure provides more information, hence improving analysts' forecast accuracy for suppliers. We expect that customer data asset information disclosure can improve their information transparency, providing more information for supplier analysts. Following Ball and Shiwakumar (2005), we use the level of absolute value accrual-based earnings management (*Transparency*) to measure customer information transparency. We expect the variable *Transparency* to be negatively correlated with corporate transparency. Table 7 Panel A illustrates the results, and the regression coefficient of *CusDA* is -0.753, which is significantly negative and supports our conjecture.

Besides, we further examine whether the customer data asset information disclosure supplements the financial reporting information of suppliers, therefore enhances suppliers' information transparency. We use two measurements. Firstly, if suppliers' information transparency is low, the information asymmetry between suppliers and analysts is high. It may be more costly for analysts to acquire firm-specific information, and analysts may consider information from other sources, such as customer information, to make forecasts. Therefore, we expect that the lower information transparency of the supplier, the stronger the impact of customer data asset information on analyst earnings forecast accuracy. We use supplier accrual-based earnings management (*Accrual*) as our indicator, and split the sample into two subgroups by median value. Table 7 Panel B supports our conjecture. Specifically, the coefficient on *CusDA* is -0.854 and statistically significant at the 5% level in the high-accruals subsample, while the coefficient is -0.372 and insignificant in the low-accruals subsample. The difference between the two groups is statistically significant.

Moreover, we expect that the less supplier forward-looking information obtained, the more important customer data asset information is to analysts. We use voluntary performance forecast (*Forward*) as an indicator, and Forward equals 1 if suppliers provide voluntary performance forecasts, and 0 otherwise. We conjecture that when suppliers do not issue voluntary performance forecasts, the disclosure of customer data asset information can further improve the accuracy of analysts' predictions. Table 7 Panel C reports the regression results. The coefficient of *CusDA* is -0.843 and significant when suppliers do not issue voluntary performance forecasts (*Forward = 0*), supporting our conjecture. The difference between the two groups is statistically significant. These results suggest that customer data assets may provide more incremental and forward-looking information and alleviate information asymmetry, thereby improving forecast accuracy.

Table 7. Does customer data asset disclosure provide more information?

Panel A: Customer data asset information and customer information transparency

VARIABLES	***Transparency***
CusDA	**−0.753*** **(−1.69)**
Controls	Yes
Constant	Included
Year and Firm Fixed Effect	Yes
Observations	1,131
Adjusted R-squared	0.551

Panel B: Customer data asset disclosure, supplier information transparency and analysts' accuracy

	FERROR	
VARIABLES	***(1)*** ***High Accruals***	***(2)*** ***Low Accruals***
CusDA	**−0.854**** **(−1.98)**	**−0.372** **(−0.44)**
Controls	Yes	Yes
Constant	Included	Included
Year and Firm Fixed Effect	Yes	Yes
Observations	746	439
Adjusted R-squared	0.657	0.394
p-value	0.000***	

Panel C: Customer data asset disclosure, supplier forward looking information and analysts' accuracy

	FERROR	
VARIABLES	**(1)** ***Forward = 1***	**(2)** ***Forward = 0***
CusDA	**–1.209** **(–1.6)**	**–0.843*** **(–1.66)**
Controls	Yes	Yes
Constant	Yes	Yes
Year and Firm Fixed Effect	Included	Included
Observations	732	453
Adjusted R-squared	0.579	0.476
p-value	0.008***	

Notes: This table presents the results of the effects of customer data asset information disclosure on information transparency. Panel A presents the results of the effects of customer data asset information disclosure on customer information transparency. Following Ball and Shiwakumar (2005), *Transparency* reflects the extent of corporate information disclosure. Panel B presents the results of the effects of customer data asset information disclosure on supplier information transparency. Panel C presents the results of the effects of customer data asset information disclosure on forward-looking information provision. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Source: authors' calculations

4.5.2 Does customer data asset disclosure signal better firm performance?

In this section, we validate the second channel. We propose that higher levels of customer data asset information disclosure are associated with improved signaling for customer future performance, which is informative of supplier future earnings. As data asset information offers precise, detailed insights into customers' future operational performance and strategic direction (Wei et al., 2025; Sun and Du, 2024), it thus influences suppliers' production planning, inventory management, and investment decisions in terms of supply chain spillover effects, ultimately improving supplier performance (Li et al., 2024). As a result, analysts become more predictable and have less uncertainty, and accordingly produce superior forecasts for supplier firms when their customers disclose more data asset information. We use Tobin's Q to measure suppliers' firm performance. The estimated results are reported in Table 8 Panel A, and the regression coefficient of *CusDA* is 17.46, which is significantly positive and supports our conjecture.

In addition, we expect that when customers exhibit lower business risk and better performance, analysts are likely to put more effort into collecting information about these customers, and this increased attention leads to more accurate forecasts for suppliers. Following Cornaggia, Krishnan, and Wang (2017), we use profit volatility (*VOLROA*) to capture firm-level business risks, and split the sample into two subgroups by median value. Table 6 Panel B supports our conjecture, showing that analyst forecast accuracy is more significant when customers have lower business risks. The coefficient of *CusDA* is -0.89 in the *LowROAVOL* group and significant at the 10% level. Additionally, customer firm performance is measured by customers' Tobin's Q (Tobin's Q), and we split the sample into two subgroups by the median value. Table 8 Panel C reports the regression results. The coefficient on *CusDA* is significantly negative for firms with *High Tobin's Q* ($\beta = -0.614$, $t = -1.72$). The difference between the two subsamples is statistically significant ($p = 0.05$). These results support our expectation that analysts produce superior performance when customers have better firm performance.

Table 8. Does customer data asset disclosure signal better firm performance?

Panel A: Customer data asset information disclosure and suppliers' firm performance

VARIABLES	***FP***
CusDA	**17.46*** (3.34)**
Controls	Yes
Constant	Included
Year and Firm Fixed Effect	Yes
Observations	1,185
R-squared	0.42

Panel B: Customer data asset information disclosure, supplier business risk and analysts' accuracy

	FERROR	
VARIABLES	**(1)** ***High ROAVOL***	**(2)** ***LowROAVOL***
CusDA	**0.291** **(0.65)**	**−0.89*** **(−1.93)**
Controls	Yes	Yes
Constant	Yes	Yes
Year and Firm Fixed Effect	Included	Included
Observations	606	579
R-squared	0.78	0.6
p-value	0.024**	

Panel C: Customer data asset information disclosure, customer firm performance and analysts' accuracy

	FERROR	
VARIABLES	**(1)** ***High Tobins'Q***	**(2)** ***Low Tobins'Q***
CusDA	**−0.614*** **(−1.72)**	**0.432** **(1.20)**
Controls	Yes	Yes
Constant	Yes	Yes
Year and Firm Fixed Effect	Included	Included
Observations	615	570
R-squared	0.861	0.856
p-value	0.05**	

Notes: This table presents the results of the effects of customer data asset information disclosure on firm performance. Panel A presents the results of the effects of customer data asset information disclosure and supplier firm performance. The suppliers' firm performance is measured by Tobin's Q. Panel B presents the results of the effects of customer data asset information disclosure and customer business risks. Following Cornaggia, Krishnan, and Wang (2017), we use profit volatility (*VOLROA*) to capture firm-level business risks. Panel C presents the results of the effects of customer data asset information disclosure and customer firm performance. We use Tobin's Q to measure firm performance. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Source: authors' calculations

4.6 Role of supply chain stability and customer concentration

Firstly, we examine the role of supply chain stability. Guan, Wong, and Zhang (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. Specifically, we propose that more stable relationships bring more effective information sharing and greater complementarity between suppliers and customers. Stable supply chain relationships enable analysts to gain deeper insights into customer operations, strategic decisions, and financial performance. Consequently, analysts can better anticipate customer demand patterns and operational outcomes, thereby significantly reducing the costs and efforts associated with acquiring and interpreting customer-related information. Based on this, this paper predicts that the more stable the customer, the greater the impact of customer earnings news on analysts' earnings forecast accuracy.

Following Zhang et al. (2025), customer stability (*Stability*) is measured by the average number of times each of the top five customers appeared in the previous year. We partitioned the sample into two groups (i.e., the less stable group with the value of Stability lower than the sample median and the more stable group with the value of Stability greater than the sample median) and estimated the regressions separately using the two sub-samples. The result is shown in Table 9 Panel A; we find that the coefficient on CusDA is -0.641 and statistically significant at the 10% level in the *More Stable* group. The difference is statistically significant.

Secondly, we measure customer concentration (*Concentration*) by the sum of the squares of the top five customers' sales to total sales. When a supplier has a higher concentration ratio, it indicates a significant portion of its revenues depends on a limited number of customers; therefore, customers become more important. As these customers become more critical to the supplier's survival and profitability, the supplier typically becomes more transparent about its business operations, financial conditions, and forecasts. Analysts, therefore, gain better visibility into the supplier's financial health, operational strategies, and future earnings potential.

Hence, we propose stronger effects for high customer concentration. We also partitioned the sample into two groups by median (the low concentration group with the value of customer concentration lower than the sample median and the high concentration group with the value of customer concentration greater than the sample median). Table 9 Panel B shows that the coefficient on *CusDA* is -0.792 and statistically significant at the 5% level in *High Concentration* group, while the coefficient is -0.146 and insignificant in *Low Concentration* group. The difference is statistically significant ($p = 0.027$).

Table 9. Role of supply chain stability and customer concentration

Panel A: Role of supply chain stability

	FERROR	
VARIABLES	**(1)** ***More Stable***	**(2)** ***Less Stable***
CusDA	**−0.641*** **(−1.76)**	**5.426**** **(2.67)**
Controls	Yes	Yes
Constant	Yes	Yes
Year and Firm Fixed Effect	Yes	Yes
Observations	734	451
R-squared	0.541	0.920
p-value	0.014**	

Panel B: Role of customer concentration

	FERROR	
VARIABLES	**(1)** ***High Concentration***	**(2)** ***Low Concentration***
CusDA	**−0.792**** **(−2.00)**	**−0.146** **(−0.17)**
Controls	Yes	Yes
Constant	Yes	Yes
Year and Firm Fixed Effect	Yes	Yes
Observations	616	569
R-squared	0.571	0.531
p-value	0.027**	

Notes: This table presents the results of the role of supply chain stability and customer concentration. Panel A reports the results in regard to customer importance (measured by *Stability* and *Concentration*). Detailed variable definitions are summarized in Appendix 3. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Source: authors' calculations

4.7 Does the effect of customer data asset disclosure vary across industries?

Moreover, we examine whether the effect of customer data asset disclosure varies across industry types by classifying the samples into high-tech (*TechTech*) and non-high-tech (*NonTechTech*) firms. We expect that data assets are the main products, profit sources, and strategic priorities for high-tech firms. Therefore, high-tech firms tend to accumulate more data assets and to disclose more data asset-related information. Besides, such information is more informative when disclosed by high-tech customers. As a result, we expect that the spillover effect of customer data asset disclosure on supplier analyst forecast is more pronounced when customers are high-tech firms. The regression results are reported in Table 10. For high-tech customers (Column 1), the *CusDA* coefficient is -1.299 and significant at the 1% level, suggesting analysts may pay more attention to data asset information when customers are high-tech firms.

Table 10. Does the effect of customer data asset disclosure vary across industries

	FERROR	
VARIABLES	**(1)** ***HighTech***	**(2)** ***NonHighTech***
CusDA	**−1.299***** **(−2.73)**	**−0.141** **(−0.24)**
Controls	Yes	Yes
Constant	Included	Included
Year and Firm Fixed Effect	Yes	Yes
Observations	448	737
R-squared	0.598	0.530
p-value	0.036**	

Notes: This table presents the results of testing the effect of customer data asset information disclosure on supplier analysts' forecast error across high-tech and non-high-tech firms. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Source: authors' calculations

4.8 Does customer data asset disclosure bring less analyst forecast dispersion?

Further, we expect that more data asset disclosures reduce information asymmetry and uncertainty, enabling analysts to base their forecasts on more objective and consistent data rather than on assumptions or subjective interpretations. As a result, analysts' evaluations of supplier firms become more aligned, leading to lower forecast dispersion. This study refers to the measurement method of Hope (2003), using the variance of analyst forecast values to measure *cap F cap D cap I cap S cap P end subscript sub, i, t, end subscript and* adopting company-level analyst forecast dispersion. Table 11 reports the regression results, which support our expectation. Specifically, the coefficient on *CusDA* is -0.323 and is statistically significant at the 10% level, suggesting that the disclosure of customer data asset information can improve the information environment and reduce analyst forecast dispersion.

Table 11. Does customer data asset disclosure bring less analyst dispersion?

VARIABLES	*FDISP*
CusDA	**−0.323*** **(−1.68)**
Controls	Yes
Constant	Yes
Year and Firm Fixed Effect	Yes
Observations	1,085
R–squared	0.372

Notes: This table presents the results of testing the effect of customer data asset information disclosure on supplier analysts' forecast dispersion. ***, **, and * indicate significance levels of 1%, 5%, and 10%.

Source: authors' calculations

5. Conclusions and discussions

Using data from Chinese listed firms between 2010 and 2024, we find that data asset information disclosures enhance information transparency and reduce information asymmetry, as well as signal customer firm performance, and are informative to suppliers' future earnings. These disclosures ultimately lower supplier analysts' forecast errors. The findings are robust to various endogeneity and robustness checks. The effects are more pronounced for firms with stable supply chain relationships, higher customer concentration, and when customers belong to high-tech industries. Our findings emphasize the importance of data asset disclosures in enhancing information transparency and reducing information asymmetry in supply chains, and have significant implications for firms, analysts, and policymakers.

This study has several empirical contributions. First, we provide new empirical evidence on the economic consequences of data asset disclosure from a supply chain perspective. Prior research has mainly examined how data asset information affects investor judgment and market efficiency (Li et al., 2022; Sun and Du, 2024; Wei et al., 2025; Luo, 2025). However, these studies fail to explore the information spillover effects along the supply chain. This paper finds that customer data asset disclosure can enhance information transparency of customer firms and is informative about suppliers' future earnings, therefore improving analysts' forecast accuracy for suppliers. On the other hand, this study extends the research on voluntary disclosure and analyst behavior in the digital economy. Existing studies find that non-financial information improves analyst forecast accuracy (Dhaliwal et al., 2012; Muslu et al., 2019). However, in the digital economy, data asset information becomes more informative and useful. By providing empirical evidence on how customer data asset information disclosure affects supplier analysts' forecast accuracy, this paper enriches the literature on analysts' information demand in the digital economy.

Based on prior empirical results, this study has the following practical implications. Firstly, it underscores the importance for firms to strengthen the disclosure of data asset information. Data asset disclosure is not only a future trend in information dissemination but also a strategic initiative to enhance financing capabilities. Therefore, firms should disclose information related to data assets more actively and transparently, establish clear data asset disclosure policies, and integrate these into the corporate governance structure. Besides, to enhance the effectiveness of the disclosure, firms should focus on the information verifiability and comprehensibility. Further, the findings of this study are likely to extend beyond the Chinese context. The application and disclosure of data assets are becoming increasingly common in firms worldwide, and the declining value relevance of financial statements in the evolving digital economy is a global trend. Therefore, the insights offered from this study are expected to be relevant and valuable in stock markets in other countries.

Moreover, as supply chains become more complex and interconnected, they are an important source of differentiation and competitive advantage for firms. The findings of this study are therefore timely. This paper investigates the importance of customer data asset information disclosure in improving supply chain information environments, suggesting that customer information disclosure can be beneficial. To reduce information asymmetry between management and stakeholders, firms should prioritize enhanced supply chain information disclosure as a strategic tool for improving market confidence and operational transparency. Further, firms should adopt comprehensive disclosure frameworks that detail supplier relationships, customer concentrations, and supply chain risks, particularly in sectors such as mining, agriculture, and manufacturing where supply chain stability is crucial.

This paper also provides a reference for regulators to develop a more practical and effective customer information disclosure policy, while improving the transparency of information in the capital markets. On the one hand, the government should fully recognize the importance and value relevance of data asset information for external information users, clarify the definition, classification, and valuation rules of data assets, as well as encourage enterprises to disclose data asset-related information. On the other hand, the government should recognize the role of supply chain management in firm development, accelerate the development of supply chain coordination platforms, and facilitate the accurate and timely transmission of information from customers to suppliers.

However, this study still has potential limitations. Firstly, this paper uses a text analysis method to analyze firms' data asset information disclosure. Although this approach is relatively reasonable for textual information, existing measures of data asset disclosure mainly focus on text mining and the quantity of disclosure. This could not capture the value of data asset information. Future research may attempt to design a comprehensive indicator system to measure the information value of enterprise data asset disclosure. Secondly, the sample size is restricted by the availability of customer information. Although the Heckman two-stage method was used to address the sample selection bias issue, the possibility that this affects the generalizability of the research conclusion still exists. Future research may incorporate more comprehensive enterprise customer data to avoid this problem. Thirdly, this study is limited to the Chinese institutional setting, which may reduce the generalizability of the findings. As the importance of data and data assets is widely recognized across the globe, cross-country comparisons with different digitalization levels would be valuable. Further research may conduct cross-country comparative studies, enhancing the external validity and generalizability of findings.

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Data Availability

Data will be made available on request.

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Appendices

Appendix 1. Key Words of Data Asset Disclosure

Key words	Data asset; Data resource; Data source; Big Data; Massive data; Data analysis system; Data sharing; Data platform; Data mining; Information resource; Knowledge base

Source: authors' processing

Appendix 2. Data Asset Disclosure Examples

Stock code	Original disclosure	Key words
300168	By leveraging cloud computing, big data, artificial intelligence, cybersecurity, and smart parks, the firm explored the inherent value of data resources, improved decision-making and operational efficiency through information integration and data governance, as well as transformed data resource into core strategic data asset	Data resource; Data asset;
002777	The company's "Medical Disease Diagnosis and Treatment Pathway Knowledge Base and Medical Expense Analysis System" has been listed as one of the first data asset products on the Guangzhou Data Exchange.	Knowledge Base; Data asset;
301299	The firm collects massive data in the commodity sector, and establishes a big data platform through data mining and data analysis, which transforms data resources into information services and consulting products, becoming the core strategic assets of the firm.	Massive data; Data mining; Data resource;
002570	Through the establishment of data platform and databases, the company integrates various information resource, transforms information resource into data resources, and forms corporate data assets. These assets provide a decision-making basis for optimizing products and services, reducing costs, and controlling risks.	Data platform; Information resource; Data assets;
600074	By integrating a data analysis system with a cloud-based technology platform, the company consolidates, mines, and utilizes massive data generated by smart hardware, extracting commercially valuable information resources. On this basis, it has developed data products and services for application scenarios such as customized information delivery and e-commerce and has realized the monetization of data value through scenario-based marketing.	Data analysis system; Massive data;

Source: authors' processing

Appendix 3. Variable Definitions

Variable	Variable Definitions
FERROR	The absolute value of the difference between mean of analysts' forecast and true value divided by share price of the beginning of year.
CusDA	The frequency of disclosure of data assets information in the annual reports.
Size	Natural logarithm of total assets for supplier firm.
ROA	The ratio of net profits to total assets for supplier firm.
Lev	The ratio of total debts to total assets for supplier firm.
StarAnal	Natural logarithm of star analyst coverage plus one for supplier firm.
Intan	Natural logarithm of intangible assets for supplier firm.
INST	The percentage of shares held by institutional investors for suppliers.
Top1	The shareholding ratio of the largest shareholder of supplier firm.
IT	The proportion of supplier executives have IT background
Digital	Digital transformation index which is acquired from CSMAR.
CusIntan	Natural logarithm of intangible assets for customer firm.
CusIT	The proportion of customer executives have IT background.
CusDigital	Customer digital transformation index which is acquired from CSMAR.
Custincrt	The purchasing ratio of customers.
SC	The average of customer concentration and supplier concentration.
CusDA2	The natural logarithm of frequency of data assets related vocabulary in annual report of customer firm.
FERROR2	The absolute value of the difference between mean of analysts' forecast and true value divided by share price of the end of year. $FERROR_{i,t} = \frac{\lvert Ave\_FEPS_{i,t} - MEPS_{i,t} \rvert}{\lvert EndPrice_{i,t} \rvert}$
CEOshares	Customer CEO's shareholding ratio.
Dual	An indicator variable which is equal to 1 if the customer firm's CEO is also the chairman and 0 otherwise.

Age	The average age of customer executives.
Female	The proportion of female executives
Overseaback	The proportion of executives with overseas backgrounds Equals to 1 if customer executives have oversea background.
CUSID	The average data assets information disclosure frequency of the same year-industry excluding company's own data.
CUSPRV	The average asset information disclosure level of customers province-year level.
L.DA	The data asset information disclosure level is lagged by one period.
Transparency	The extent of corporate information disclosure following Ball and Shiwakumar (2005).
Accrual	The extent of corporate information disclosure following Dechow (1995).
Forward	Equals to 1 if suppliers provide voluntary performance forecast and 0 otherwise.
FP	The suppliers' firm performance, which is measured by Tobin's Q.
VOLROA	The profit volatility following Cornaggia, Krishnan, and Wang (2017).
Stability	The average number of times each of the top five customers appeared in the previous year.
Concentration	The sum of squared of top five customer sales to total sales.
HighTech	Equals to 1 if customer firm belongs to the high-technology industries, and 0 otherwise.
FDISP	The forecast dispersion of analysts for supplier. Following the measurement method of Hope (2003), we use variance of analyst forecast values to measure *FDISP* and adopt company-level analyst forecast dispersion.

Source: authors' processing