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RESEARCH ARTICLE

Positive Externalities of Credit Ratings: Customer Downgrades, Supplier Performance, and Investor Perception

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ABSTRACT

This study examines how a change in information about a customer's creditworthiness affects responses to a supplier's financial information, focusing on earnings response coefficients (ERCs). We use a major customer's credit rating downgrade (CCRD) as a change to the information environment. We find that suppliers' ERCs are weaker following a CCRD, consistent with reduced persistence and growth opportunities. We find evidence supporting investors' reactions: after the downgrade, suppliers are more likely to experience a deterioration in customer relationships, reduced operational efficiency and investment and fewer growth opportunities. These findings highlight a positive externality of credit ratings that are created for debt holders, but are also useful to other stakeholders.

JEL Classification: M14, G41

1 | Introduction

Credit rating agencies focus on assessing the quality of debt for the firms they rate. These agencies are sophisticated analysts and provide a public signal of the private information they gather from management (Bonsall et al. 2025). The public nature of credit ratings makes them useful not only to investors of the rated firms but also to investors of related firms (Alldredge et al. 2022). Prior research finds that the disclosure and operational choices of a major customer can significantly influence a supplier's operational efficiency (Chen et al. 2019; Patatoukas 2012; Raman and Shahrur 2008). Notably, a supplier's operational and financial performance can be disrupted in the event of a customer bankruptcy (Dai et al. 2021; Hertzel et al. 2008; Kolay et al. 2016). In light of such potential risks, the Financial Accounting Standards Board (FASB) has recently proposed rule changes to increase disclosure of supplier finance programmes to help investors evaluate risks associated with supply chain lending (FASB 2022). We examine whether investors use changes in a customer's creditworthiness when evaluating the supplier's financial performance. Our results provide insight into the positive externalities provided by credit rating agencies and the mosaic of information that investors use when evaluating a firm (Cheynel and Levine 2020; Li et al. 2023).

A recent study by Alldredge et al. (2022) provides evidence that customer credit rating downgrades result in significant negative shocks to the stock price of supplier firms, suggesting that credit shocks can impact investors of upstream suppliers. Their findings show that the effect is associated with the strength of the customer–supplier linkage and market anticipation of downgrades, as well as other firm- and industry-level factors. While Alldredge et al. (2022) document immediate stock price reactions to customer credit downgrades, our study focuses on whether changes in a customer's creditworthiness affect investor perceptions of the supplier's earnings information. We examine the supplier's earnings response coefficient (ERC) to investigate how investors interpret a customer's information. ERCs provide a straightforward method for measuring informativeness and represent a clear link between accounting information and market pricing of that information.[1] Because suppliers are intrinsically connected to their major customers, we examine whether perceptions of riskiness, persistence and growth trickle down the supply chain.

We use customer credit rating downgrades (CCRD) as a shock to information about the creditworthiness of customers. Credit ratings are widely available, and recent research indicates that investors are cognizant of a customer's credit rating (Alldredge et al. 2022). Changes in credit ratings provide a clear, directional shock to the riskiness of a supplier's earnings and are particularly informative for suppliers whose major customers are large public companies. In addition, they reflect private information obtained during the rating process (Gounopoulos and Pham 2017). Similar to the effect of a company's own rating downgrade, we expect that suppliers' ERC will weaken when a customer experiences a rating downgrade (Billings 1999; Collins and Kothari 1989; Dhaliwal and Reynolds 1994).

We begin our investigation by examining a supplier's ERC following a CCRD with a robust set of controls and fixed effects. Our primary results are consistent with our hypothesis that the quality of a customer's credit affects the perception of a supplier's accounting information. We perform cross-sectional tests for when a customer's rating may be more significant to a supplier. We use propensity score matching to provide evidence that the disclosure of the rating matters beyond observable signals of distress. We split the sample into pairs where the customer accounts for at least 15% of the supplier's revenue and find that the ERC effect is concentrated in the sample with more important customers. Additionally, we follow Kolay et al. (2016) and divide the sample using prior relationship-specific investments. If a supplier has invested heavily in the supply chain relationship, then we expect higher switching costs and the customer's financial condition to have a stronger effect on the customer itself. Consistently, we find that the ERC effect is concentrated in the subsample of suppliers that have created more specialised products for their customers.

Analysts are important capital market participants and act as intermediaries between firms and investors (Bradshaw 2011). Analysts often follow firms along the supply chain and interpret information for investors in the customer or supplier firm (Guan et al. 2015; Luo and Nagarajan 2015). Analyst disagreement is a signal of uncertainty about future opportunities and expectations. We test and find that the suppliers' analysts have more dispersed forecasts following a CCRD. This result is consistent with a higher risk for the supplier.

Next, we turn our attention to changes in the customer–supplier relationship and effects on supplier fundamentals following a CCRD.[2] We examine the continuation of the customer–supplier relationship and find that the relationship is more likely to deteriorate following a CCRD, complementing prior studies on factors influencing the duration of the customer–supplier relationship (Bauer et al. 2018). This fundamental change in the source of the supplier's revenue is consistent with increased risk, as well as lower persistence and fewer growth opportunities.

While suppliers may not want to end a relationship with, or reduce sales to, a riskier customer, they may be hesitant to make non-fungible investments. Suppliers often make notable relationship-specific investments for their major customers. These investments can lead to hold-up problems that firms have tried to mitigate through a variety of mechanisms (Costello 2013; Grossman and Hart 1986; Grove et al. 2024; Raman and Shahrur 2008). A CCRD is a clear sign of increased risk to the supplier's investment. Therefore, we test whether suppliers change investment levels following a CCRD. Consistent with our expectations, we observe a strong and negative relationship between CCRDs and supplier investment.

Next, we provide evidence related to the supplier's growth opportunities. Billings (1999) notes that weaker ERCs for a firm following its own rating downgrade are highly attributable to reduced growth opportunities. We regress Tobin's *Q* on CCRD and find that suppliers have significantly lower Q following a CCRD, which provides some evidence that growth opportunities play a role in the weaker ERCs following a CCRD.

Finally, the supplier is likely to have already made substantial capital investments for its major customer. We expect that these assets may become less productive than originally planned, leading to lower firm efficiency. To test this expectation, we examine a number of firm efficiency ratios (Patatoukas 2012; Radhakrishnan et al. 2014). We find that suppliers exhibit lower ratios—specifically, return on assets, profit margin and asset turnover—following a CCRD. These results provide consistent evidence with the findings that investors place less weight on supplier earnings surprises, as these key efficiency ratios decline following the downgrades.

Taken together, our results provide evidence that investors perceive a firm's own information differently when additional information is available about a closely related firm (Madsen 2017). We add to the existing literature by examining investor integration of changes in a customer's downside risk. Madsen (2017) focuses on customer equity returns and information acquisition, as opposed to information assessment following credit risk. Alldredge et al. (2022) focus on the initial investor response to a CCRD, but do not examine investor reactions to the customer's own information or subsequent real effects. Investigation of a supplier's performance following a CCRD provides validity to the main results in our paper and those found in prior research.

We also contribute to the rich literature on earnings response coefficients. ERCs have long been an important indicator of how investors use and understand accounting information (Beaver 1968; Collins and Kothari 1989). We extend this literature by considering how a customer's downside risk affects investors' perception of earnings. Echoing the FASB's effort to enhance transparency about financing along the supply chain, we provide timely policy implications by highlighting the linkage between customer default risk and investors' perception of suppliers' earnings information. This provides further insight into the broader mosaic of information that contextualises a company's information (Cheynel and Levine 2020; Hsiao et al. 2024). Firm-specific disclosures will likely complement the use of third-party information for investor decision making.

Last but not least, we provide new information about the use of credit ratings by suppliers and their investors. To our knowledge, we are the first to provide evidence of reduced investment and degrading firm fundamentals following a CCRD. Prior research uses other metrics as proxies for a company's financial distress in their studies. For example, Hertzel et al. (2008) and Kolay et al. (2016) find evidence suggesting that financial distress travels down the supply chain using customer bankruptcy. Lian (2017) uses distance to default as an indicator of financial distress, developed by Merton (1974). CCRDs are the result of an expert analysis of credit risk, contain private information, and are created primarily for debt holders (Bonsall et al. 2025). Credit rating downgrades are less severe events than bankruptcies. Examining how a CCRD is perceived by the supplier and its investors highlights a positive externality of the credit rating industry: it provides timely information that allows stakeholders to respond to changes in risk before more extreme outcomes occur.

2 | Background

2.1 | The Customer–Supplier Link

Supply chain relationships are an important aspect of both an individual business and the economy as a whole and have been widely studied in many academic areas (Lambert and Cooper 2000). Prior research in accounting has focused on the value of information along the supply chain. For example, Olsen and Dietrich (1985) investigate the link between retailer sales reports and their suppliers' security returns. They find that large deviations from expected sales are associated with supplier returns, indicating that investors use the information of economically linked firms when valuing a supplier. Cohen and Frazzini (2008) examine major customers' earnings releases and subsequent supplier returns, finding that customer information leads to predictable supplier returns in the following months. Building on their findings, Madsen (2017) accounts for the information acquisition around the supplier's earnings announcement. If investors obtain more customer reports prior to the supplier's earnings announcement, the supplier's stock is priced more efficiently. In addition, customer-level information also influences debt market outcomes. Kim et al. (2015) and Files and Gurun (2018) consider the use of customer information by bank lenders. Both customer earnings performance and customer bankruptcy are associated with the loan contract terms that a borrower receives from the lenders.

Related research in corporate finance has examined how a customer's financial condition can directly impact a supplier's own operations. Hertzel et al. (2008) provide evidence that suppliers have negative abnormal returns during periods of their major customers' financial distress, proxied by eventual bankruptcy. However, Kolay et al. (2016) find that these negative stock returns are experienced by suppliers that have high switching costs in acquiring new customers. Suppliers tied to firms that are likely to reorganise do not experience the same negative returns. Lian (2017) provides complementary evidence that suppliers to financially distressed firms are more likely to experience distress themselves, which works harmoniously with the results in Files and Gurun (2018).

More recently, Alldredge et al. (2022) examine how investors respond to a customer's credit downgrade. They find that a downgrade of a major customer leads to concurrent, significant negative market reaction for the supplier, even outside the context of customer bankruptcy. Their analysis shows that the stock return decrease depends on firm- and industry-level factors, including the strength of the customer–supplier relationship and how much the market anticipates the downgrade. They also document that suppliers are more likely to experience a downgrade themselves following a customer downgrade, showing financial contagion within supply chains. Our study is closely related but distinct. Although Alldredge et al. (2022) focus on immediate stock price decreases around the credit downgrade event, we focus on a different question: whether a customer downgrade influences the informativeness of the supplier's earnings. Specifically, we examine how a CCRD affects investor response to supplier earnings surprises, as captured by ERCs. This study addresses changes in earnings quality, persistence and investor perception, rather than the immediate shock associated with the downgrade. We extend Alldredge et al. (2022) by providing a forward-looking perspective on the consequences of CCRDs for suppliers' financial information environment and provide new insights into how credit risk information flows across firms within supply chain relationships.

2.2 | Credit Ratings

A credit rating is a quantitative assessment that represents the creditworthiness of a company. Essentially, it predicts the likelihood that the borrower will fulfil its financial obligations in a timely manner (Akins 2018). Credit rating agencies have access to a company's management and provide a public signal of private information obtained from management (Bonsall et al. 2025).

Credit rating agencies (e.g., Standard & Poor's [S&P], Moody's, Fitch) assign credit ratings. These ratings range from high investment grade (indicating low credit risk) to below investment grade (indicating higher credit risk). In the S&P and Fitch systems, *AAA* is the highest rating, while *D* indicates default.

The determination of a credit rating is based on a thorough analysis of financial history and health, including past credit behaviour, economic conditions and the borrower's overall financial condition. Higher ratings generally enable borrowers to issue bonds at a lower interest rate and favourable terms, reflecting the lower risk perceived by lenders. Conversely, a lower credit rating suggests higher risk and typically results in higher borrowing costs for the debtor.

Credit rating downgrades can significantly influence corporate operations and market perceptions. Goh and Ederington (1993) provide evidence that rating downgrades linked with new information can adversely affect a company's stock performance. Odders-White and Ready (2006) find that credit ratings affect stock liquidity, particularly the adverse selection component of liquidity. Moreover, Kang (2022) finds that firms facing the risk of a credit rating downgrade tend to engage in fewer acquisitions, likely due to increased financing costs and a more cautious investment strategy induced by potential downgrades.

3 | Hypothesis Development

3.1 | Customer Credit Rating Downgrade and Supplier ERCs

ERCs have traditionally been used to understand how investors interpret firm information (Beaver 1968; Collins and Kothari 1989). ERC measures the sensitivity of a firm's stock return to its unexpected earnings, estimated using the regression of cumulative abnormal returns on earnings surprise. Collins and Kothari (1989) provide a foundational framework for understanding the cross-sectional and temporal variation in ERCs. They show that the ERC is a function of several factors, including the risk-free interest rate, the riskiness of the firm and the growth and persistence of its earnings. Their model improves the specification of the earnings–returns relation and explains why ERCs differ across firms and time. Building on this framework, we examine whether changes in a customer's creditworthiness can affect investor perceptions of a supplier's earnings persistence, risk and its earnings quality.

Prior research supports the notion that credit risk plays a role in shaping ERCs. Dhaliwal and Reynolds (1994) find that firms with higher default risk tend to have lower ERCs, indicating that investors place less weight on earnings surprises of riskier firms. Billings (1999) revisits this issue and shows that the effect of credit ratings on ERCs weakens when including an earnings growth parameter. This suggests that the relationship between credit rating and ERC, as documented by Dhaliwal and Reynolds (1994), may reflect investor expectations about future growth captured by credit risk proxies. Furthermore, Dichev and Piotroski (2001) find that following a credit rating downgrade of its own, a firm exhibits weaker fundamentals and negative long-run returns, with much of the abnormal return occurring around earnings announcements. Their findings suggest that credit downgrades can reduce earnings informativeness by signalling lower earnings persistence and increased risk.

Although these studies focus on a firm's own credit risk, we consider whether creditworthiness about a downstream customer may have a similar effect on the upstream supplier. When a major customer experiences a downgrade, it signals increased financial risk and reduced growth prospects. This change in customer credit quality is likely to affect the supplier's expected performance. Given the close economic ties between suppliers and their major customers, such a shock influences how investors view the persistence of the supplier's earnings.

For example, if a customer accounts for a substantial share of a supplier's sales, then that customer's financial distress and the risk of losing that customer may reduce the supplier's revenue stability. In response, the supplier may hold more cash to alleviate the induced operating risk (Itzkowitz 2013), reduce debt, or forego investment opportunities. These adjustments can limit the supplier's future growth. Suppliers are also more likely to receive a downgrade following their primary customer's downgrade (Alldredge et al. 2022; Lian 2017). These findings suggest that changes in customer credit risk can ripple through the supply chain and affect how investors evaluate the informativeness of suppliers' earnings.

Intuitively, if a major customer has an elevated default risk and lower growth expectations, the supplier's earnings may become less persistent and less informative. Following the model in Collins and Kothari (1989), we use ERCs to capture investor perceptions of supplier earnings informativeness and examine whether changes in a customer's credit rating affect the perceptions. Specifically, we expect customer credit rating downgrades (CCRDs) to be associated with lower supplier ERCs. We state our hypothesis as follows:

Hypothesis 1. *Investors have a weaker response to unexpected earnings following a customer's credit rating downgrade.*

3.2 | Moderating Factors

One major reason why a CCRD can influence a supplier firm's earnings properties is the economic interdependence between the supplier and its customers. The relationship is crucial because supplier companies face potential financial setbacks when they lose customers, especially those who are important to the suppliers' business operations. Research by Hertzel et al. (2008) and Kolay et al. (2016) indicates that customer losses are particularly severe when the customer plays a critical role in the supplier's economic ecosystem. In addition, many studies in supply chain recognise the relevance of important business relationships, defined by the strength of the customer-supplier linkage (e.g., Chiu et al. 2019; Itzkowitz 2013; Lian 2017). Consequently, investors may interpret the loss as more impactful in the event of a major customer rating downgrade. As a result, we expect the negative effects of a CCRD on a supplier's earnings to be more pronounced when the supplier has a higher degree of reliance on the customer, stated as follows:

Hypothesis 2. *The change in investor response to unexpected earnings following a CCRD is more pronounced when the customer is more important to the supplier.*

Moreover, firms that sell specialised products or services tend to rely more heavily on their customers. This dependency is particularly evident in businesses where the products or services are tailored to meet specific customer needs (Itzkowitz 2013). Such investments are often difficult to redeploy for the general market and will result in sunk costs if the customer relationship ends or is threatened by a CCRD. Consequently, for suppliers with specific investments in their products, the business operations and earnings informativeness may be more sensitive to customer default risk.

In the literature, this type of investment is referred to as relationship-specific investment (RSI). Titman and Wessels (1988) are among the first to identify uniqueness as a product characteristic that suggests job-specific skills and expenditures firms incur. Following this notion, a number of studies use research and development (R&D) expense or its variations to measure RSIs (Banerjee et al. 2008; Bowen et al. 1995; Dhaliwal et al. 2016; Kale and Shahrur 2007; Lee et al. 2020; Raman and Shahrur 2008). Evident in the literature, R&D expenses capture a firm's RSIs in proprietary technologies or specialised production that help produce unique products for customers. Following prior research (e.g., Kolay et al. 2016), we use a well-established proxy, R&D expense, to measure suppliers' relationship-specific investments. We expect that when a supplier has made significant RSIs, the customer's credit downgrade will have a greater effect on suppliers' earnings informativeness. This leads to the following hypothesis:

Hypothesis 3. *The change in investor response to unexpected earnings following a CCRD is more pronounced when the supplier has made significant relationship-specific investments in its products.*

4 | Data, Empirical Model and Variables

4.1 | Data Construction

Since we are interested in examining the influence of the customer company's credit rating on the supplier company's earnings response coefficient, we build a sample around the supplier company's quarterly earnings announcement. We start our sample construction with firm quarterly financial data between 2002 and 2019 from Compustat.[3] Then, we merge the sample with customer information from Compustat Segment files and customer credit rating information from the Wharton Research Data Services (WRDS) Bond Database. Lastly, we obtain the analyst forecast information from the Institutional Brokers Estimates System (I/B/E/S). Our final sample includes 56,492 quarterly earnings announcements for each customer and supplier pair. Table 1 presents the summary statistics and sample distribution by year and by industry.

4.2 | Empirical Model

We begin by examining the market reaction to earnings surprises for a supplier company when its customer experiences a downgrade in the corporate bonds, and we estimate the following standard ERC regression model:

$$\begin{aligned} CAR\,[0,2] = \; & \alpha_0 + \alpha_1 Customer\ Downgrade \times SUE + \alpha_2 SUE \\ & + \alpha_3 Customer\ Downgrade + \Sigma\beta Controls \\ & + \Sigma\lambda Controls \times SUE + Fixed\ Effects + \epsilon \end{aligned} \tag{1}$$

where the dependent variable *CAR* [0,2] is the three-day cumulative market-adjusted return for a firm around its earnings announcement, and *SUE* is the standardised unexpected earnings. It is computed as the difference between reported earnings per share (EPS) and the analyst consensus EPS scaled by the quarter-end stock price (e.g., DeHaan et al. 2015). Other variables in the model are detailed subsequently. The coefficient of interest is α_1 on the interaction term (*Customer Downgrade* × *SUE*), which measures the market response to the supplier company's earnings announcement. A negative (positive) value of α_1 implies that customer credit downgrade is associated with a muted (enhanced) investor response to earnings. We use robust standard errors clustered by earnings announcement date.

4.3 | Variables

4.3.1 | Credit Ratings and Customer Downgrade

For each customer company in our sample, we obtain the monthly ratings of corporate bonds from three sources (i.e., Moody's, Standards & Poor's and Fitch) compiled by the WRDS Bond Returns database.[4] A rating represents the agency's opinion on an issuer's overall capacity to meet its financial obligations. We identify a credit downgrade event for a customer if its rating on the supplier's earnings announcement date is lower than its rating 6 months before.[5] We denote it with an indicator variable *Customer Downgrade* being one; and zero otherwise.

The six-month window balances timeliness with responsiveness to information about related parties. This allows credit rating agencies time to disseminate information and investors time to process the change and observe a quarterly earnings cycle. The timing is appropriate, as both ratings agencies and market responses along the supply chain are often delayed (Cohen and Frazzini 2008; Covitz and Harrison 2004). Additionally, a six-month lookback period helps smooth out short-term noise and capture more persistent changes in issuers' credit quality, which is meaningful for suppliers' long-term planning and for investor reassessment of earnings quality. As such, the six-month downgrade window balances timeliness and rating responsiveness, aligns with the timeframe suppliers use to interpret customer financial health, and therefore is informative for capturing investor responses to customer credit changes.

4.3.2 | Earnings Response Coefficient

We use *ERCs* to capture investors' responses to current earnings information, an important aspect of earnings quality. The *ERC* is commonly known as the slope coefficient in a regression of abnormal stock returns on a measure of the standardised earnings surprise. Following prior studies (e.g., DeHaan et al. 2015), we compute the standardised unexpected earnings (*SUE*) as the difference between reported earnings per share (EPS) and the analyst consensus EPS scaled by the quarter-end stock price. The cumulative abnormal return (*CAR*) is the raw buy-and-hold return adjusted using the market-value-weighted returns. To capture immediate market reaction, we compute *CAR* over a 3-trading-day window [0,2] around the earnings announcement.

4.3.3 | Control Variables

We include as control variables an array of company characteristics that are likely covariates associated with the market response to earnings surprises. In our model, we include *Size* (the natural logarithm of total assets) and *MTB* (market-to-book ratio) because larger and growth companies tend to have a more pronounced market response to unexpected earnings (Collins and Kothari 1989). We then include several variables related to

TABLE 1 | Summary statistics.

Panel A: Descriptive summary						
	N	**Mean**	**Std. Dev.**	**p25**	**p50**	**p75**
CAR[0,2]	56,492	−0.002	0.098	−0.054	−0.001	0.052
SUE	56,492	0.001	0.012	−0.001	0.001	0.003
Customer Downgrade	56,492	0.137	0.344	0.000	0.000	0.000
Size	56,492	6.913	1.689	5.697	6.820	8.062
MTB	56,492	3.237	5.675	1.392	2.272	3.870
Friday	56,492	0.054	0.226	0.000	0.000	0.000
ReportingLag	56,492	33.167	10.795	26.000	32.000	38.000
NumAnalyst	56,492	11.439	8.798	5.000	9.000	16.000
Qtr4	56,492	0.206	0.404	0.000	0.000	0.000
Customer Size	56,492	10.796	1.230	9.989	10.828	11.742

Panel B: Sample distribution by fiscal year			
Fiscal year	**Frequency**	**Percent**	**Cumulative percent**
2002	1454	2.57	2.57
2003	2529	4.48	7.05
2004	2751	4.87	11.92
2005	2863	5.07	16.99
2006	3149	5.57	22.56
2007	3170	5.61	28.17
2008	3183	5.63	33.81
2009	3123	5.53	39.34
2010	3427	6.07	45.40
2011	3510	6.21	51.62
2012	3361	5.95	57.57
2013	3714	6.57	64.14
2014	3908	6.92	71.06
2015	3754	6.65	77.70
2016	3541	6.27	83.97
2017	3412	6.04	90.01
2018	3232	5.72	95.73
2019	2411	4.27	100
Total	56,492	100	

Panel C: Sample distribution by industry			
Fama–French industry classification			
Industry classification	**Frequency**	**Percent**	**Cumulative percent**
Consumer nondurables—food, tobacco, textiles and apparel, leather, toys	4240	7.51	7.51
Consumer durables—cars, TV's, furniture, household appliances	3919	6.94	14.44

(Continues)

TABLE 1 | (Continued)

Panel C: Sample distribution by industry			
Fama–French industry classification			
Industry classification	**Frequency**	**Percent**	**Cumulative percent**
Manufacturing—machinery, trucks, planes, office furniture, paper and commercial printing	6859	12.14	26.58
Energy—oil, gas, coal extraction and products	4977	8.81	35.39
Chemicals and allied products—chemicals, petroleum refining, plastics and pharmaceutical products	1400	2.48	37.87
Business equipment—computers, software and electronic equipment	15,010	26.57	64.44
Telecommunications—telephone and television transmission	1264	2.24	66.68
Wholesale, retail—wholesale, retail and some services (laundries, repair shops)	1841	3.26	69.94
Healthcare—healthcare, medical equipment and drugs	10,740	19.01	88.95
Other—mines, construction, transportation, hotels, business services and entertainment	6242	11.05	100
Total	56,492	100	

earnings announcements. *Friday* is an indicator variable that equals one if earnings are announced on a Friday. Prior studies suggest the responses to earnings announcements on Fridays are generally weaker and slower due to investor inattention (e.g., DellaVigna and Pollet 2009). *Qtr4* is an indicator for a company's fourth quarter in a fiscal year. We include it to control for the confounding effect of the fiscal year-end earnings announcement around the fourth quarter earnings announcement. *ReportingLag* is the number of days between quarter-end and earnings announcement date. Prior studies find that the stock price reaction is likely higher when earnings are reported on a more timely basis (e.g., Chambers and Penman 1984). Moreover, we include *NumAnalyst*, the number of sell-side financial analysts following a company during a fiscal year. Since analyst following denotes investor attention, which is directly associated with market responses, companies with higher *NumAnalyst* are likely to have stronger *ERC*. As large customers are generally more important to the suppliers and the consequences of credit downgrading are likely to be more significant, we include *Customer Size* (the natural logarithm of the customer company's total assets) to control for customer characteristics and customer importance. Appendix A provides detailed definitions for the variables used in our analysis.

To account for the marginal effects of the controls on investors' response to earnings surprises, we add the interaction terms of the control variables and *SUE*. Moreover, we include time (year–month) fixed effects to control for the macroeconomic trend. We also include the supplier–customer fixed effects to control for unobservable time-invariant characteristics within individual supplier–customer pairs. In the alternative specification, we use supplier and customer fixed effects.

4.4 | Descriptive Statistics

Our final sample comprises 56,492 supplier–customer-year-quarter observations from 2002 through 2019. It includes 1629 unique supplier firms, with each supplier paired with an average of 2.58 customers. These sample characteristics are similar to those reported in recent studies examining comparable time periods (e.g., Agca et al. 2022). Table 1 provides the descriptive statistics for selected variables. Panel A indicates that about 13.7% of the observations experienced a downgrade in our sample. About 5.4% of the earnings announcements are on a Friday, and the lag of earnings reporting averages 33 days after the quarter-end. On average, there are 11.4 analysts following each company. About 20.6% of the sample is for the fourth quarter earnings announcement. Customer companies are generally much larger than supplier companies, as reflected in the average log of total assets (*Size* is 6.9 for suppliers vs. 10.8 for customers). By and large, the descriptive statistics of firm characteristics and the attributes of earnings announcements in our sample are consistent with those reported in prior studies.

Panel B reports the sample distribution by year. The numbers of observations in each of the fiscal years between 2002 and 2019 are well balanced, ranging from 1454 in 2002 to 3908 in 2014. Panel C presents the sample distribution by industry. Nearly 27% of the observations are in business equipment industries such as computers and software. The healthcare industry and manufacturing companies have about 19% and 12% of the observations, respectively.

5 | Empirical Results

5.1 | ERC Analysis

We predict that the market reaction to earnings surprises for a supplier will be muted when its customer experiences a downgrade in corporate bonds. Table 2 presents the results from estimating Equation (1). In column 1 of Table 2, the coefficient of SUE is positive and significant, consistent with the notion that a positive earnings surprise leads to an increase in stock

TABLE 2 | Customer downgrade and ERC.

	(1)	(2)
	***CAR*[0,2]**	***CAR*[0,2]**
Customer Downgrade × SUE	−0.291**	−0.262*
	(−2.05)	(−1.94)
SUE	2.543***	2.503***
	(3.53)	(3.64)
Customer Downgrade	0.003*	0.002*
	(1.95)	(1.73)
Size	−0.015***	−0.013***
	(−7.24)	(−6.36)
MTB	−0.001***	−0.000***
	(−4.30)	(−3.91)
Friday	−0.004	−0.003
	(−0.95)	(−0.78)
ReportingLag	−0.000	−0.000
	(−0.30)	(−0.34)
NumAnalyst	−0.000	−0.000
	(−0.15)	(−0.15)
Qtr4	−0.000	−0.000
	(−0.09)	(−0.05)
Customer Size	−0.002	−0.001
	(−1.09)	(−0.59)
Size × SUE	0.114**	0.115**
	(2.40)	(2.46)
MTB × SUE	0.009	0.011
	(0.83)	(1.05)
ReportingLag × SUE	−0.031***	−0.030***
	(−3.02)	(−3.04)
Friday × SUE	−0.447*	−0.466**
	(−1.87)	(−2.00)
NumAnalyst × SUE	0.011	0.011
	(0.72)	(0.74)
Qtr4 × SUE	−0.375	−0.392
	(−1.19)	(−1.27)
Customer Size × SUE	0.002	0.001
	(0.04)	(−0.03)
Observations	56,492	56,492
Adj. R-squared	0.08	0.10
Fixed effects	Customer–supplier, month	Customer, supplier, month

Note: Standard errors are clustered by the reporting date of quarterly earnings. t-statistics are in parentheses. *, ** and *** indicate significance at the 0.1, 0.05 and 0.01 levels, respectively. Constant terms are not reported. Variables are defined in Appendix A.

price around the earnings announcement date and vice versa. More importantly, the estimated coefficient α_1 on (*Customer Downgrade × SUE*) is negative and significant at the 5% level ($\alpha_1 = -0.291$ with t-statistic $= -2.05$), suggesting that when a customer experiences a credit downgrade on its corporate bonds, the earnings responses in the stock market for the supplier are muted. In terms of economic magnitude, a downgrade in a customer's credit rating reduces the supplier's earnings response by 11.4% on average.[6]

As an additional robustness check, we replace the supplier–customer fixed effects with supplier and customer fixed effects and re-estimate Equation (1). Column 2 presents the result. The coefficient α_1 continues to be significantly negative at the 10% level ($\alpha_1 = -0.262$ with t-statistic $= -1.94$), further corroborating our prediction that a customer credit downgrade can negatively influence market responses to supplier earnings news.

Our conclusion is also robust to the two-way clustering of standard errors by supplier and earnings announcement date. In the two-way clustered regressions, the coefficients on (*Customer Downgrade × SUE*) remain negative and statistically significant at the 10% level (untabulated), and the economic magnitude remains unchanged. This additional robustness check confirms that our results are not driven by a specific clustering choice.

Furthermore, we examine how the primary results are affected by different cumulative abnormal return (*CAR*) windows. We use *CAR* [−1,1], *CAR* [−3,3], and *CAR* [0,5] as the dependent variable and rerun Equation (1). The results (untabulated) show that the coefficients on the interaction term (*Customer Downgrade × SUE*) are consistently negative and similar in magnitude across all alternative *CAR* windows. The interaction term is statistically significant at the 10% level when using *CAR* [−1,1] and *CAR* [0,5], and just above the 10% threshold when using *CAR* [−3,3]. This pattern of results aligns with expectations. *CAR* [0,2], our main specification, is a short and focused window that captures the core informational impact of earnings announcements with minimal noise. The longer window *CAR* [0,5], and the window that includes pre-announcement trading days, *CAR* [−1,1], may both dilute the effect of customer downgrades on the earnings-return relation, showing a slightly less significant result. Finally, *CAR* [−3,3] is both prolonged and includes preannouncement days, showing the weakest customer downgrade effect. Overall, our main result is robust to alternative *CAR* window choices, further supporting Hypothesis 1.

5.1.1 | Propensity Score Matching

Our ERC analysis may be subject to endogeneity concerns. For example, certain supplier characteristics—such as operating efficiency or product quality—may simultaneously influence the market reaction to its earnings surprises and the likelihood of a customer's credit rating downgrades. On the other hand, a firm experiencing a credit downgrade may self-select to become a customer of a supplier firm that has decreased ERCs. These concerns raise the possibility that the relationship between CCRD and ERC is driven by selection on observable firm characteristics.

To mitigate the concerns, we use propensity score matching (PSM) to construct a matched sample that is comparable along key observable firm attributes. As noted in Shipman et al. (2017), PSM controls for observable factors and has the benefit of reducing model dependency by forming treatment and control groups that are closely matched. In this sense, PSM is well suited to our setting, where the treatment (i.e., an event of CCRD) may reflect differences in firm characteristics that could be difficult to model. We identify treatment firms with a customer credit downgrade and match them to control firms without such a downgrade. The matching is performed within the same year and based on the covariates used in our baseline ERC analysis. This step helps to balance the observable firm characteristics between the treatment and control groups and isolates the effect of CCRD on the supplier ERC.

We estimate Equation (1) on the matched sample and report the results of PSM analysis in Table 3. Post-matching *t*-tests (untabulated) show no statistically significant differences in key observable characteristics between treatment and control groups. Importantly, the estimated coefficient on the interaction term (*Customer Downgrade* × *SUE*) remains negative and significant at the 10% level in both model specifications. These results further support our main finding and suggest that the negative relationship between CCRD and supplier ERC is unlikely to be driven by selection on observable factors.

While PSM reduces selection bias arising from observables, we acknowledge that it has limitations in addressing unobserved time-varying factors (Shipman et al. 2017). Nonetheless, several steps in our analysis help mitigate the concern. Our propensity score matching is conducted within the same fiscal year, and both baseline and PSM regressions include fixed effects, which control for time-specific and unobservable factors. Taken together, these efforts help minimise endogeneity concerns and strengthen the findings in ERC analysis.

5.1.2 | Instrumental Variable Analysis

Our main tests assume that customer credit downgrades are exogenous to supplier outcomes. However, one might argue that rating agencies could incorporate supplier-level signals when assessing a customer's creditworthiness. For example, a supplier's operational or financial distress might feed back into the customer's own downgrade. This reverse causality threat would bias our estimates if a customer's CCRD partly reflects supplier problems.

When credit rating agencies assign or revise ratings, they focus on the company's own financial metrics and industry outlook. If a single supplier does not play a significant role in the customer firm's revenue generation, rating agencies will not consider supply chain risks. In our sample, the average *Size*—measured as the natural logarithm of total assets—is 6.9 for suppliers versus 10.8 for customers (Table 1). This implies that customers are generally about 49 times larger. Given this disparity, it is highly unlikely that supplier distress would affect a customer's credit rating. In addition to our conceptual argument, we further address the reverse-causality concerns empirically. We follow Lewbel (2012) and implement a heteroskedasticity-based instrumental variable (IV) approach. Rather than identifying an external instrument,

TABLE 3 | Customer downgrade and ERC—propensity score matching.

	(1)	(2)
	***CAR*[0,2]**	***CAR*[0,2]**
Customer Downgrade × *SUE*	−0.283*	−0.248*
	(−1.75)	(−1.66)
SUE	2.162**	2.029**
	(2.06)	(2.05)
Customer Downgrade	0.002	0.002
	(1.19)	(1.40)
Size	−0.015***	−0.012***
	(−4.88)	(−4.50)
MTB	−0.001***	−0.001***
	(−3.48)	(−3.09)
Friday	−0.003	−0.004
	(−0.57)	(−0.82)
ReportingLag	0.000	0.000
	(0.57)	(0.37)
NumAnalyst	−0.000	−0.000
	(−0.64)	(−0.41)
Qtr4	−0.003	−0.003
	(−0.82)	(−0.63)
Customer Size	0.000	0.001
	(0.10)	(0.48)
Size × *SUE*	0.146**	0.138**
	(2.09)	(2.04)
MTB × *SUE*	0.003	0.002
	(0.19)	(0.16)
ReportingLag × *SUE*	−0.022	−0.021
	(−1.52)	(−1.57)
Friday × *SUE*	−0.494	−0.551*
	(−1.51)	(−1.76)
NumAnalyst × *SUE*	−0.005	−0.005
	(−0.26)	(−0.23)
Qtr4 × *SUE*	−0.512	−0.454
	(−1.21)	(−1.12)
Customer Size × *SUE*	0.002	0.011
	(0.03)	(0.17)
Observations	23,233	23,626
Adj. *R*-squared	0.09	0.10
Fixed effects	Customer–supplier, month	Customer, supplier, month

Note: Standard errors are clustered by the reporting date of quarterly earnings. *t*-statistics are in parentheses. *, ** and *** indicate significance at the 0.1, 0.05 and 0.01 levels, respectively. Constant terms are not reported. Variables are defined in Appendix A.

Lewbel's (2012) approach generates synthetic instruments from within the existing model using heterogeneity in the error term of the first-stage regression model. This method has been adopted by contemporary studies to mitigate endogeneity problems (Agca et al. 2022; Hasan et al. 2021, 2022) and is particularly useful when external instruments are not readily available. Since the endogenous variables are *Customer Downgrade* and the interaction term *Customer Downgrade × SUE*, we obtain the predicted values for them in the first-stage regression using generated instruments as well as controls from the main model.[7]

The second-stage regression results are reported in Table 4. We find that the coefficients on *Customer Downgrade × SUE* are negative and significant at the 10% level. The results are similar to our baseline specification, thus supporting our hypothesis that customer credit downgrade leads to a weaker market response to supplier unexpected earnings. Importantly, since the results are based on an instrumental variable approach in which the endogenous CCRD is instrumented, the concern of reverse causality—that credit rating downgrades may be influenced by supplier-specific issues—is substantially mitigated.

TABLE 4 | Customer downgrade and ERC—instrumental variables.

	(1)	(2)
	***CAR*[0,2]**	***CAR*[0,2]**
Customer Downgrade(fitted)×SUE	−0.247*	−0.218*
	(−1.79)	(−1.65)
SUE	2.577***	2.531***
	(3.59)	(3.69)
Customer Downgrade(fitted)	0.018***	0.016***
	(2.73)	(2.70)
Size	−0.015***	−0.012***
	(−7.16)	(−6.28)
MTB	−0.001***	−0.000***
	(−4.23)	(−3.85)
Friday	−0.003	−0.003
	(−0.87)	(−0.70)
ReportingLag	−0.000	−0.000
	(−0.32)	(−0.37)
NumAnalyst	−0.000	−0.000
	(−0.22)	(−0.23)
Qtr4	−0.000	−0.000
	(−0.11)	(−0.07)
Customer Size	−0.004*	−0.002
	(−1.69)	(−1.50)
Size×SUE	0.113**	0.114**
	(2.38)	(2.45)
MTB×SUE	0.009	0.011
	(0.88)	(1.09)
ReportingLag×SUE	−0.031***	−0.030***
	(−3.01)	(−3.04)
Friday×SUE	−0.443*	−0.463**
	(−1.86)	(−1.98)
NumAnalyst×SUE	0.010	0.010
	(0.70)	(0.71)
Qtr4×SUE	−0.380	−0.395
	(−1.21)	(−1.28)
Customer Size×SUE	−0.001	−0.001
	(−0.02)	(−0.02)
Observations	56,492	56,492
Adj. R-squared	0.08	0.10
Fixed effects	Customer–supplier, month	Customer, supplier, month

Note: Standard errors are clustered by the reporting date of quarterly earnings. t-statistics are in parentheses. *, ** and *** indicate significance at the 0.1, 0.05 and 0.01 levels, respectively. Constant terms are not reported. Variables are defined in Appendix A.

5.2 | Cross-Sectional Analyses

5.2.1 | The Effect of Customer Importance

If the observed ERC effect on the supplier is attributable to a CCRD event with the customer, then the effect should be strong when the customer is significant to the supplier, and a change in the customer's business is impactful to the supplier's cash flows (Farrell and Klemperer 2007). To test this conjecture (Hypothesis 2), we compute the percentage of customer sales (i.e., sales made to a customer scaled by the supplier's total sales) and use it as a proxy for customer importance. A large share indicates a more important customer to the supplier. We then split the sample based on whether the percentage of customer sales is greater than or equal to 15% and re-estimate Equation (1) using the two subsamples.[8] Table 5 presents the results. Columns 1 and 3 use the subsample with customer sales greater than 15% of its supplier's total sales. Column (1) includes customer–supplier as one of the fixed effects while column 3 includes customer and supplier fixed effects. We note that among the more important customers (i.e., sales% ≥ 15%), their CCRD events continue to exert negative effects on the market reactions to the suppliers' earnings announcements. The coefficient α_1 is −0.578 and −0.588, respectively, with a 5% level of statistical significance. In contrast to this result, columns 2 and 4 suggest that less important customers' CCRD events are not significantly associated with the suppliers' earnings response, as the coefficient α_1 is negative but insignificant in both columns. This evidence is consistent with our hypothesis that the ERC effect is concentrated in the subsample where individual customers play a more central role in suppliers' businesses, indicating a more severe effect of CCRD.

5.2.2 | The Effect of Supplier Product Specialisation

We next explore cross-sectional variation with respect to the supplier's product specialisation. This test is motivated by the observation that a supplier who has made specific investments (RSIs)

TABLE 5 | Customer importance and ERC.

	(1)	(2)	(3)	(4)
	***CAR*[0,2]**	***CAR*[0,2]**	***CAR*[0,2]**	***CAR*[0,2]**
	***CustSale* ≥ 15%**	***CustSale* < 15%**	***CustSale* ≥ 15%**	***CustSale* < 15%**
Customer Downgrade × SUE	−0.578**	−0.119	−0.588**	−0.079
	(−2.48)	(−0.69)	(−2.56)	(−0.49)
SUE	1.631*	3.325***	1.666*	3.162***
	(1.66)	(3.54)	(1.73)	(3.53)
Customer Downgrade	0.007**	0.002	0.006*	0.001
	(1.98)	(0.96)	(1.77)	(0.63)
Size	−0.016***	−0.018***	−0.014***	−0.014***
	(−4.63)	(−6.74)	(−4.29)	(−6.02)
MTB	−0.000*	−0.001***	−0.000	−0.001***
	(−1.81)	(−4.34)	(−1.63)	(−3.94)
Friday	−0.007	−0.002	−0.006	−0.001
	(−1.36)	(−0.45)	(−1.36)	(−0.29)
ReportingLag	−0.000	0.000	−0.000	0.000
	(−0.91)	(0.05)	(−0.69)	(0.08)
NumAnalyst	0.000	−0.000	−0.000	0.000
	(0.32)	(−0.09)	(−0.04)	(0.07)
Qtr4	−0.002	0.000	−0.002	0.000
	(−0.41)	(0.01)	(−0.51)	(0.00)
Customer Size	−0.000	−0.003	0.003	−0.001
	(−0.01)	(−1.12)	(0.55)	(−0.37)
Observations	12,539	43,455	12,816	43,489
Adj R-squared	0.09	0.09	0.10	0.11
Controls × SUE	Yes	Yes	Yes	Yes
Fixed effects	Customer–supplier, month	Customer–supplier, month	Customer, supplier, month	Customer, supplier, month

Note: Columns 1 and 3 report the OLS regression results for the subsample with customer sales ≥ 15%. Columns 2 and 4 report the OLS regression results for the subsample with customer sales < 15%. Standard errors are clustered by the reporting date of quarterly earnings. t-statistics are in parentheses. *, ** and *** indicate significance at the 0.1, 0.05 and 0.01 levels, respectively. Constant terms are not reported. Variables are defined in Appendix A.

TABLE 6 | Supplier specific investment and ERC.

	(1)	(2)	(3)	(4)
	CAR[0,2]	*CAR*[0,2]	*CAR*[0,2]	*CAR*[0,2]
	R&D > 0	*R&D* = 0	*R&D* > 0	*R&D* = 0
Customer Downgrade × SUE	−0.409**	−0.158	−0.370**	−0.173
	(−2.18)	(−0.78)	(−2.09)	(−0.89)
SUE	0.269	5.359***	0.411	5.295***
	(0.28)	(5.13)	(0.45)	(5.25)
Customer Downgrade	0.003	0.002	0.003	0.001
	(1.51)	(0.73)	(1.62)	(0.31)
Size	−0.016***	−0.017***	−0.014***	−0.014***
	(−5.80)	(−4.73)	(−5.40)	(−4.27)
MTB	−0.001***	−0.001**	−0.001***	−0.001**
	(−3.61)	(−2.31)	(−3.36)	(−2.21)
Friday	−0.010**	0.003	−0.009**	0.003
	(−2.36)	(0.47)	(−2.01)	(0.47)
ReportingLag	0.000	−0.000	0.000	−0.000*
	(1.06)	(−1.37)	(1.14)	(−1.66)
NumAnalyst	0.000	−0.000	0.000	−0.000
	(0.36)	(−0.60)	(0.39)	(−0.71)
Qtr4	−0.004	0.006	−0.004	0.007
	(−1.18)	(0.95)	(−1.13)	(1.09)
Customer Size	−0.003	−0.003	−0.002	0.000
	(−1.06)	(−0.99)	(−1.31)	(0.12)
Observations	31,667	24,662	31,734	24,689
Adj R-squared	0.08	0.12	0.10	0.13
Controls × SUE	Yes	Yes	Yes	Yes
Fixed effects	Customer–supplier, month	Customer–supplier, month	Customer, supplier, month	Customer, supplier, month

Note: Columns 1 and 3 report the OLS regression results for the subsample where supplier R&D is greater than 0. Columns 2 and 4 report the OLS regression results for the subsample where supplier R&D equals 0. Standard errors are clustered by the reporting date of quarterly earnings. *t*-statistics are in parentheses. *, ** and *** indicate significance at the 0.1, 0.05 and 0.01 levels, respectively. Constant terms are not reported. Variables are defined in Appendix A.

in the products for its customers relies heavily on the customers' business health. Consequently, when the customer experiences financial hardship, the expected return on specialised product development declines as sales become less likely and the customised products are difficult to repurpose. This places the supplier at increased operational risk with uncertainties in the future. As a result, we predict that the effect of CCRD on the supplier's earnings response is more pronounced among suppliers that have made significant investments in their products (Hypothesis 3).

Following Kolay et al. (2016), we use R&D expenses to measure customer–supplier relationship-specific investments.[9] We construct two subsamples based on whether supplier-specific investments are greater than zero and re-estimate Equation (1). Table 6 reports the results. Columns 1 and 3 are for the subsample with R&D expenses greater than zero. We note that the coefficients of interest α_1 in these two columns are both significantly negative at the 5% level, while they are insignificant in columns 2 and 4 for suppliers that do not have R&D expenses. These results are consistent with our prediction that the effect of customer CCRD on suppliers' ERC is concentrated among suppliers who have made specific investments in the products for their customers.

5.3 | Additional Analyses

5.3.1 | CCRD and Analyst Perceived Uncertainty

In our baseline analyses, we examine investors' perception of the supplier company's earnings information following a CCRD. Oftentimes, investors rely on financial analysts, an information intermediary, to provide and interpret information for investment purposes (Bradshaw 2011). Analysts are sophisticated capital market participants with access to more comprehensive information than the general investing public, including industry-specific details and supply chain information that may affect the perception of the focal firms they follow (Guan et al. 2015; Luo and Nagarajan 2015). We next explore analysts' perceptions of earnings information of supplier firms after a CCRD event.

We use analyst earnings forecast dispersion, *Dispersion*, to capture the collective analysts' perceptions of the firm they follow. *Dispersion* is computed as the standard deviation of quarterly EPS forecasts estimated by all analysts in the next quarter. The level of analyst forecast dispersion reflects the uncertainty of a company's future performance (Givoly and Lakonishok 1984; Zhang 2006). Hence, we test how analysts interpret a customer's credit downgrade by examining analyst forecast dispersion following a CCRD. Specifically, we estimate the following model:

$$Dispersion = \alpha_0 + \alpha_1 Customer\ Downgrade + \Sigma\beta Controls + Fixed\ Effects + \epsilon \tag{2}$$

where *Dispersion* is quarterly analyst forecast dispersion for the next quarter.[10] *Controls* is a vector of control variables that may affect *Dispersion*, including the natural logarithm of total assets (*Size*), market-to-book ratio (*MTB*), the number of days difference between fiscal quarter end and earnings announcement date (*ReportLag*), the number of sell-side financial analysts (*NumAnalyst*), an indicator for the fourth quarter (*Qtr4*), an indicator for a Friday earnings announcement (*Friday*) and the natural logarithm of the customer's total assets (*Customer Size*). Fixed effects include customer–supplier pair (or customer and supplier) and time fixed effects.

Table 7 reports the results of regressing *Dispersion* on *Customer Downgrade* and the control variables. In both columns, the coefficients on *Customer Downgrade* are positive and statistically significant at 1%. In terms of economic significance, the dispersion of analyst forecasts increases by 9% following a customer credit downgrade, on average. This evidence is consistent with the notion that, when the customer firm experiences a credit downgrade, analysts following the supplier firm perceive greater uncertainty about the supplier's future prospects and increased risk for investors.

5.3.2 | Deterioration of Customer–Supplier Relationship

We next examine whether CCRDs are associated with a weakening of the customer–supplier relationship. If the decline in ERCs following a CCRD reflects investor concern about the stability of a supply chain partnership, we would expect the customer–supplier relationship to diminish in importance or, in some cases, end altogether. That is, increased customer risk can lead to a deterioration in the economic importance of the relationship.

Following Bauer et al. (2018), we construct a measure that captures whether a customer–supplier relationship continues to meet the 10% disclosure threshold required by SFAS 131 (discussed further below) and use this as our outcome variable. Specifically, we estimate the following regression model:

$$SC\_Stop = \alpha_0 + \alpha_1 Customer\ Downgrade + \Sigma\beta Controls + Fixed\ Effects + \epsilon \tag{3}$$

where *Customer Downgrade* is an indicator variable that equals one if a company (the customer) experiences a credit downgrade in fiscal year t, and *SC_Stop* is an indicator variable that equals one if the customer–supplier relationship is no longer reported in the next fiscal year $t+1$ and zero otherwise.[11]

We estimate Equation (3) using both an ordinary least squares (OLS) model with supplier, customer and year fixed effects, and a logit model with industry and year fixed effects. The fixed effects used in this analysis differ from those in the main regression. In the main test, month fixed effects are important for capturing market-wide news cycles and market reactions to earnings, while in the relationship deterioration test, year fixed effects are more appropriate to examine longer-run relationship changes. For logistic regression, we use industry fixed effects in place of the high-dimensional customer and supplier fixed effects used in the OLS model, as a reasonable and tractable alternative. Control variables follow Bauer et al. (2018), including customer–supplier relationship characteristics, as well as firm-level controls for both the customer and supplier.

Table 8 reports the results. The number of observations in both models is smaller than in the main regression because this analysis examines relationship changes at the customer–supplier-year level, whereas the main test is conducted at the quarterly level using credit rating updates. Columns 1 and 2 show that the coefficient on *Customer Downgrade* is positive and statistically significant in both models. These findings suggest that a customer downgrade is associated with a higher likelihood that the customer–supplier relationship falls below the SFAS 131 reporting threshold in the subsequent year. In terms of economic significance, a CCRD increases the likelihood of a relationship drop by approximately 31%.[12] This analysis corroborates our main results. It identifies a potential channel through which customer credit downgrades affect investor perception of the supplier's earnings. Specifically, if a CCRD decreases the stability of the business relation, investors would adjust their view of the supplier's earnings persistence, which is consistent with a reduced ERC.

5.3.3 | Effect on Investment Activities

Next, we turn our attention to the investment levels and growth opportunities of suppliers following a CCRD event. We anticipate that suppliers pay close attention to the customer's financial disclosures and other capital market information (Chen et al. 2019; Chiu et al. 2019; Radhakrishnan et al. 2014). Therefore, suppliers can adjust their operations in response to observing a CCRD.[13]

Investment activities constitute an important aspect of firm performance. Supplier investments are often directly tied to major customers and may be scaled back when a customer's future performance appears uncertain (Chen et al. 2019; Costello 2013; Raman and Shahrur 2008). As a result, in the event of a CCRD, the supplier may suffer from reduced sales to the affected customer and, in turn, limited resources, leading to reduced investments in future growth. We expect a negative relation between CCRD and the supplier's investments. Following Gulen and Ion (2016), we measure *Investment* as the capital investments scaled by total assets and estimate the model in Equation (5) in the analysis.

TABLE 7 | Customer downgrades and supplier analyst forecast dispersion.

	(1)	(2)
	Dispersion	***Dispersion***
Customer Downgrade	0.003***	0.004***
	(3.44)	(3.72)
Size	0.014***	0.014***
	(4.99)	(5.18)
MTB	−0.000	−0.000
	(−0.46)	(−0.03)
Friday	−0.004**	−0.004**
	(−2.14)	(−2.11)
ReportingLag	0.000***	0.000***
	(3.93)	(3.81)
NumAnalyst	−0.000*	−0.000*
	(−1.77)	(−1.40)
Qtr4	−0.002**	−0.002*
	(−2.11)	(−1.93)
Customer Size	0.002	0.000
	(0.99)	(0.21)
Observations	46,196	46,326
Adj R-squared	0.48	0.46
Fixed effects	Customer–supplier, month	Customer, supplier, month

Note: Dispersion is the standard deviation of quarterly analyst EPS forecasts in the next quarter. Standard errors are clustered by supplier. t-statistics are in parentheses. *, ** and *** indicate significance at the 0.1, 0.05 and 0.01 levels, respectively. Constant terms are not reported. Variables are defined in Appendix A.

To further strengthen our analysis, we examine the effect of CCRD on a firm's growth opportunity using Tobin's Q. This measure has been extensively used in the accounting and finance literature as a proxy for future growth opportunities (e.g., Modi and Mishra 2011). Tobin's Q is computed as the ratio of the market value of total assets to the replacement cost of total assets, emphasising the overall valuation of the corporation. Following Gompers et al. (2003) and Kaplan and Zingales (1997), we define Tobin's Q as:

$$TobinQ_{it} = \frac{Total\ Assets_{it} + Market\ Equity_{it} - Book\ Equity_{it}}{Total\ Assets_{it}} \tag{4}$$

where $Total\ Assets_{it}$ is the total asset of firm i in fiscal year t, $Market\ Equity_{it}$ is the market value of equity for firm i in fiscal year t, and $Book\ Equity_{it}$ is the book value of equity for firm i in fiscal year t.[14]

To empirically test the influence of CCRD on supplier investment and growth opportunity, we estimate the model in Equation (5):

TABLE 8 | Customer downgrade and termination of supplier–customer relationship.

	(1)	(2)
	SC_Stop	***SC_Stop***
Customer Downgrade	0.024**	0.272***
	(2.22)	(3.16)
CustConc	−0.420***	−4.424***
	(−7.22)	(−8.76)
SuppConc	−0.025	−0.496***
	(−1.39)	(−2.92)
Tenure	0.009***	−0.063***
	(5.08)	(−5.00)
Size	−0.015	−0.203***
	(−1.35)	(−6.78)
Age	0.024**	0.001
	(1.98)	(0.33)
R&D	−0.000	0.000
	(−0.70)	(0.80)
NegFCF	0.002	0.180**
	(0.16)	(2.00)
Customer Size	−0.034*	−0.045
	(−1.79)	(−1.24)
Cust Age	0.002	0.003
	(0.07)	(1.12)
Cust R&D	0.000	0.000*
	(0.24)	(1.73)
InvTurnover	0.000	0.000
	(0.90)	(0.11)
InvHoldingPeriod	−0.233*	−0.524
	(−1.93)	(−0.90)
PP_to	0.000	0.001
	(0.04)	(0.34)
Days AR	−0.000	0.000
	(−1.10)	(0.18)
Days AP	0.000	0.001***
	(0.66)	(2.58)
Days Inv	−0.000	−0.000
	(−0.21)	(−0.05)
CAPX	0.043	0.020
	(0.31)	(0.03)

(Continues)

TABLE 8 | (Continued)

	(1)	(2)
	SC_Stop	***SC_Stop***
PM	−0.005	−0.008
	(−0.46)	(−0.13)
GM	−0.01	−0.106
	(−0.48)	(−1.11)
Observations	7772	8241
Fixed effects	Customer, supplier, year	Industry, year

Note: Column 1 reports the OLS regression results, and column 2 reports logit regression results. *CustConc* (*SuppConc*) is the customer (supplier) concentration. Tenure is the length of the customer–supplier relationship. Age is the firm age. R&D is corporate R&D investment scaled by total assets. *NegFCF* is an indicator variable set to one if the company's free cash flows is negative. *InvTurnover* is the inventory turnover ratio. *InvHoldingPeriod* is the length of the inventory holding period. *PPE_to* is the PPE turnover ratio. *Days AR* (*Days AP*/*Days Inv*) is the days of accounts receivable (accounts payable/inventory). *CAPX* is investment scaled by total assets; *PM* is the profit margin. *GM* is the gross margin. *t*-statistics are in parentheses. *, ** and *** indicate significance at the 0.1, 0.05 and 0.01 levels, respectively. Constant terms are not reported. Variables are defined in Appendix A.

TABLE 9 | Customer downgrade and investment.

	(1)	(2)
	Investment	***Investment***
Customer Downgrade	−0.001***	−0.001***
	(−4.15)	(−4.61)
Size	−0.001***	−0.001***
	(−3.09)	(−3.26)
Leverage	−0.007***	−0.007***
	(−5.64)	(−6.14)
Cash	−0.008***	−0.008***
	(−6.85)	(−7.09)
SaleGrowth	0.000	0.000
	(0.46)	(1.12)
NumAnalyst	0.000**	0.000
	(2.29)	(1.28)
Customer Size	0.001**	0.000
	(2.09)	(1.17)
Observations	54,727	54,742
Adj *R*-squared	0.73	0.72
Fixed effects	Customer–supplier, month	Customer, supplier, month

Note: Investment is calculated as capxq/atq. Standard errors are clustered by supplier. *t*-statistics are in parentheses. *, ** and *** indicate significance at the 0.1, 0.05 and 0.01 levels, respectively. Constant terms are not reported. Variables are defined in Appendix A.

$$Y = \alpha_0 + \alpha_1 Customer\ Downgrade + \Sigma\beta Controls + Fixed\ Effects + \epsilon \quad (5)$$

where the dependent variable *Y* is either Investment or *TobinQ*, denoting supplier's capital investments or its future growth opportunity, respectively. *Controls* are a set of covariates that affect a company's investment activities. Specifically, we control for firm size (*Size*), measured as the natural logarithm of total assets, as prior research has found a negative association between firm size and firm performance (Modi and Mishra 2011). We also control for cash holdings (*Cash*) and expect a positive association with firm performance due to the potential improvement of a firm's financial flexibility and cash flow projections (Opler et al. 1999). In addition, we include sales growth (*SaleGrowth*) and leverage ratio (*Leverage*) as controls, consistent with Lu and Shang (2017). We expect sales growth to correlate positively with firm investment, as higher sales may increase revenue and earnings potential. Leverage is likely to increase financial risk and therefore is expected to have a negative effect on firm performance. We also control for firm information environment using analyst coverage (*NumAnalyst*) as well as customer fundamentals using customer's total assets (*Customer Size*).

Tables 9 and 10 present the regression results using *Investment* and *TobinQ* as the respective dependent variables. In both tests,

TABLE 10 | Customer downgrade and Tobin's *Q*.

	(1)	(2)
	TobinQ	***TobinQ***
Customer Downgrade	−0.036**	−0.037***
	(−2.49)	(−2.66)
Size	−0.686***	−0.646***
	(−11.43)	(−11.71)
Leverage	−0.251*	−0.258*
	(−1.85)	(−1.82)
Cash	0.807***	0.837***
	(5.39)	(4.99)
SaleGrowth	0.074***	0.090***
	(2.99)	(3.37)
NumAnalyst	0.033***	0.036***
	(6.42)	(6.99)
Customer Size	0.001	0.011
	(0.01)	(0.41)
Observations	54,765	54,780
Adj *R*-squared	0.77	0.74
Fixed effects	Customer–supplier, month	Customer, supplier, month

Note: Standard errors are clustered by supplier. *t*-statistics are in parentheses. *, ** and *** indicate significance at the 0.1, 0.05 and 0.01 levels, respectively. Constant terms are not reported. Variables are defined in Appendix A.

the coefficient of *Customer Downgrade* is significantly negative at the 5% or 1% level. The *Investment* regression results support our prediction that suppliers reduce capital investments in the event of a CCRD, and the *TobinQ* analysis further complements our investigation by showing that these suppliers experience lower growth opportunities. The findings suggest that customer credit downgrades restrict supplier growth both through real investment decisions and market valuation.

5.3.4 | Effect on Operational Efficiency

Finally, we consider corporate operating efficiency. Intuitively, when a supplier's sales fall short of expectations due to its customer's CCRD, the business's operational efficiency is compromised. Following prior research (e.g., Radhakrishnan et al. 2014), we employ DuPont profitability ratios to measure operating performance. The DuPont profitability framework decomposes the return on assets (*ROA*) into asset turnover and profit margin ratios. The first component measures how effectively a company is using its assets to generate sales, and the second captures how much profit it makes from those sales. Since sales are likely more difficult when a customer's credit rating decreases, we expect the *ROA* and its two components are lower in the event of CCRD. To test it, we estimate the following model:

$$Efficiency = \alpha_0 + \alpha_1 Customer\ Downgrade + \Sigma\beta Controls + Fixed\ Effects + \epsilon \tag{6}$$

where *Efficiency* is one of the three efficiency measures: the return on assets (*ROA*), profit margin (*ProfitMargin*), or asset turnover ratio (*AssetTO*). We include the same set of control variables used in the investment activity analysis because they are covariates that are likely to affect firm operational performance. The coefficient of interest α_1 captures the influence of CCRD on suppliers' operating efficiency.

Table 11 presents the results, indicating that *ROA* and both of its components, profit margin and asset turnover ratio, are negatively affected by customers' CCRD. In columns 1 to 6, α_1 is negative and statistically significant at the 1% level. Taking the asset turnover ratio as an example, a CCRD event is associated with a 3% decrease in the supplier's asset turnover ratio. These results suggest that a shock to a customer's creditworthiness negatively influences the supplier's operational efficiency. Importantly, this result substantiates the shifting expectations of company fundamentals when there is a CCRD

TABLE 11 | Customer downgrade and operational efficiency.

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	***ROA***	***ProfitMargin***	***ProfitMargin***	***AssetTO***	***AssetTO***
Customer Downgrade	−0.003***	−0.003***	−0.040**	−0.043**	−0.006***	−0.006***
	(−4.88)	(−5.19)	(−2.26)	(−2.48)	(−4.79)	(−4.43)
Size	0.012***	0.010***	0.058*	0.023	−0.066***	−0.062***
	(6.30)	(6.11)	(1.94)	(0.72)	(−14.30)	(−14.64)
Leverage	−0.057***	−0.057***	−0.349**	−0.350**	−0.030***	−0.031***
	(−10.39)	(−10.34)	(−2.41)	(−2.23)	(−2.87)	(−2.91)
Cash	0.027***	0.022***	−0.104	−0.310**	−0.108***	−0.117***
	(5.02)	(4.26)	(−0.88)	(−2.12)	(−9.16)	(−9.65)
SaleGrowth	0.027***	0.027***	0.626***	0.609***	0.063***	0.062***
	(16.81)	(16.21)	(9.15)	(8.67)	(20.06)	(19.67)
NumAnalyst	−0.000***	−0.000***	−0.011***	−0.010***	0.000	0.000
	(−3.05)	(−3.05)	(−3.35)	(−2.82)	(0.34)	(0.76)
Customer Size	−0.002	−0.001**	−0.000	−0.002	0.008**	0.004**
	(−1.45)	(−2.00)	(−0.02)	(−0.09)	(2.36)	(2.04)
Observations	54,750	54,765	54,705	54,723	54,765	54,780
Adj R-squared	0.57	0.56	0.69	0.65	0.90	0.89
Fixed effects	Customer–supplier, month	Customer, supplier, month	Customer–supplier, month	Customer, supplier, month	Customer–supplier, month	Customer, supplier, month

Note: Standard errors are clustered by supplier. t-statistics are in parentheses. *, ** and *** indicate significance at the 0.1, 0.05 and 0.01 levels, respectively. Constant terms are not reported. Variables are defined in Appendix A.

event, and it further corroborates the market reactions observed in our study as well as evidence in prior studies in this line of research (e.g., Alldredge et al. 2022).

6 | Conclusion

This paper explores how changes in the creditworthiness of a major customer affect investor reactions to the supplier's own financial reporting. Specifically, we investigate the link between a customer's credit rating downgrade (CCRD) and the supplier's ERC. We find that suppliers exhibit weaker ERCs following a CCRD, consistent with investors perceiving increased risk, lower earnings persistence, and lower growth expectations (Collins and Kothari 1989; Dhaliwal and Reynolds 1994). These results are robust to propensity score matching and are more pronounced when the customer accounts for a significant portion of a supplier's sales.

We then examine how CCRDs affect the supply chain relationship and supplier operations. We find that customer–supplier relationships are more likely to deteriorate after a CCRD, as reflected by a drop below the disclosure threshold set by SFAS 131. We also find that suppliers reduce investments, experience lower operating efficiency, and have lower growth opportunities following customer downgrades. These results suggest a potential mechanism through which CCRDs reduce the informativeness of supplier earnings—consistent with the decline in ERCs we observe and the initial market reaction documented by Alldredge et al. (2022).

Our findings contribute to a broader understanding of how credit risk information travels through supply chain networks and shapes investor expectations. They highlight the role of credit rating agencies in transmitting forward-looking information, not only about the rated firm but also about economically connected counterparties. In particular, our study provides evidence that even less severe financial distress, such as customer credit downgrades rather than bankruptcy, can propagate through the supply chain, complementing earlier findings on the spillover effects of bankruptcy (Hertzel et al. 2008; Kolay et al. 2016). Investors, analysts and lenders can benefit from using customer credit ratings as early warning indicators in supplier risk assessments.

Importantly, our findings also speak to current regulatory developments. The FASB has recently issued ASU 2022–04 to enhance transparency around supplier finance programmes, requiring customer firms to disclose programme details such as key terms and outstanding obligations. Although the standard focuses on financing arrangements and does not address customer credit risk, our study shows that such risk can significantly affect supplier firm operations and investor perception. As regulators and investors seek greater visibility into supply chain-related risks, this evidence supports the broader intent of the new FASB standard to improve supply chain transparency and highlights the importance of customer financial health disclosure, complementing the FASB's reporting requirements on financing structures. Future standards could be enhanced to address financially material exposures related to customer dependency and creditworthiness that are not currently captured by existing reporting requirements.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data used in this paper is publicly available.

Endnotes

[1] See, for example, Collins and Kothari (1989) for the theoretical underpinnings for the link between earnings surprises and market reactions as well as cross-sectional variation in the ERC based on earnings riskiness, persistence and growth. See, for example, Dhaliwal and Reynolds (1994) and Billings (1999) for empirical evidence relating a firm's own default risk to these constructs.

[2] Note that we are not suggesting a causal link between ratings downgrades and supplier performance. We provide evidence consistent with rational decision-making by investors.

[3] We start from 2002 because the WRDS Bond database provides information that goes back to 2002.

[4] Bond Returns by WRDS is a novel and unique corporate bond database sourced from TRACE Standard and TRACE enhanced datasets. It contains detailed information such as bond prices, returns, yields and ratings.

[5] We consider three ratings (Moody's, Standards & Poor's and Fitch) combined when identifying a credit downgrade.

[6] The estimated coefficient for *SUE* is 2.543, and the reduction in *ERC* is calculated as $\frac{-0.291}{2.543} = -11.4\%$.

[7] In untabulated results from first-stage regression, the Kleibergen-Paap rk LM statistic indicates a p value$\ll$0.001, rejecting under-identification and confirming that the model is well-identified. The Kleibergen-Paap rk Walk F statistic also passes the weak identification test, indicating that the Lewbel (2012) generated instruments are strong. The Hansen J statistic shows a p value of 0.4205, fail to reject the null that the instruments are valid. These statistics support the relevance and validity of the synthetic instruments.

[8] Although SFAS 131 requires disclosure when a customer accounts for more than 10% of a firm's total revenue, a higher threshold, such as 15% is often used in empirical studies to capture more economically significant relationships that can influence the supplier's risk exposure. We follow prior literature in using a 15% sales threshold to identify significant customers from the supplier's perspective. For instance, Costello (2013) notes that, according to SEC, suppliers are 'substantially dependent' when contracts represent 10%–15% of the total sales. Similarly, Cen et al. (2017) apply a 15%–20% sales threshold to define principal customers and dependent supplier relationships in their empirical analysis.

[9] While not customer-specific, this measure captures a supplier's general reliance on proprietary or specialised product development, often aligned with key customers. The measure of R&D expense denotes an increased exposure to customer instability when product redeployment is limited. This approach is common in empirical settings where customer-level R&D data is typically not publicly available.

[10] In particular, we only explore EPS forecasts and require FPI to be in '6' or '7'. Dispersion is the standard deviation of forecasts made

within 90 days before the announcement dates (the REPDATS field from I/B/E/S).

[11] SFAS 131 mandates that firms disclose the identity of any customer that accounts for 10% or more of the firm's total sales. Similar to the approach in related literature (Bauer et al. 2018; Nelson and Wang 2024; Raman and Shahrur 2008), we define a deterioration in the customer-supplier relationship as the relationship falling below the 10% sales threshold for disclosure under SFAS 131. This threshold suggests a significant economic tie. We acknowledge that a drop below the threshold does not always indicate a relationship termination. As noted in Bauer et al. (2018), while we cannot directly observe full termination, a drop below the threshold signals a significant diminishing relationship. Accordingly, our test results provide evidence that CCRDs contribute to the deterioration and in some cases, potential termination of customer-supplier relationships.

[12] The coefficient in column 2 is 0.272, suggesting an odds ratio of 1.3126 ($e^{0.272}$), which is equivalent to a 31% increase in the likelihood.

[13] Although suppliers are likely aware of worsening credit conditions before the announcement of a downgrade, we focus on investments, which are typically planned over a period of several quarters. Therefore, we examine investment outcomes in the period subsequent to the CCRD.

[14] We calculate the book value of equity as (shareholders' equity + deferred taxes + investment tax credit − preferred stock).

References

Agca, S., V. Babich, J. R. Birge, and J. Wu. 2022. "Credit Shock Propagation Along Supply Chains: Evidence From the CDS Market." *Management Science* 68, no. 9: 6506–6538.

Akins, B. 2018. "Financial Reporting Quality and Uncertainty About Credit Risk Among Ratings Agencies." *Accounting Review* 93, no. 4: 1–22.

Alldredge, D. M., Y. Chen, S. Liu, and L. Luo. 2022. "The Effect of Credit Rating Downgrades Along the Supply Chain." *Review of Accounting and Finance* 21, no. 1: 1–31.

Banerjee, S., S. Dasgupta, and Y. Kim. 2008. "Buyer–Supplier Relationships and the Stakeholder Theory of Capital Structure." *Journal of Finance* 63, no. 5: 2507–2552.

Bauer, A. M., D. Henderson, and D. P. Lynch. 2018. "Supplier Internal Control Quality and the Duration of Customer–Supplier Relationships." *Accounting Review* 93, no. 3: 59–82.

Beaver, W. H. 1968. "The Information Content of Annual Earnings Announcements." *Journal of Accounting Research* 6: 67–92.

Billings, B. K. 1999. "Revisiting the Relation Between the Default Risk of Debt and the Earnings Response Coefficient." *Accounting Review* 74, no. 4: 509–522.

Bonsall, S. B., J. B. Donovan, E. R. Holzman, X. Wang, and D. G. Yang. 2025. "Do Credit Ratings Reflect Private Information About Sec Investigations?" *Accounting Review* 100: 1–24.

Bowen, R. M., L. DuCharme, and D. Shores. 1995. "Stakeholders' Implicit Claims and Accounting Method Choice." *Journal of Accounting and Economics* 20, no. 3: 255–295.

Bradshaw, M. T. 2011. "Analysts' Forecasts: What Do We Know After Decades of Work?" Available at SSRN 1880339.

Cen, L., E. L. Maydew, L. Zhang, and L. Zuo. 2017. "Customer–Supplier Relationships and Corporate Tax Avoidance." *Journal of Financial Economics* 123, no. 2: 377–394.

Chambers, A. E., and S. H. Penman. 1984. "Timeliness of Reporting and the Stock Price Reaction to Earnings Announcements." *Journal of Accounting Research* 22: 21–47.

Chen, C., J.-B. Kim, M. Wei, and H. Zhang. 2019. "Linguistic Information Quality in Customers' Forward-Looking Disclosures and Suppliers' Investment Decisions." *Contemporary Accounting Research* 36, no. 3: 1751–1783.

Cheynel, E., and C. B. Levine. 2020. "Public Disclosures and Information Asymmetry: A Theory of the Mosaic." *Accounting Review* 95, no. 1: 79–99.

Chiu, T.-T., J.-B. Kim, and Z. Wang. 2019. "Customers' Risk Factor Disclosures and Suppliers' Investment Efficiency." *Contemporary Accounting Research* 36, no. 2: 773–804.

Cohen, L., and A. Frazzini. 2008. "Economic Links and Predictable Returns." *Journal of Finance* 63, no. 4: 1977–2011.

Collins, D. W., and S. Kothari. 1989. "An Analysis of Intertemporal and Cross-Sectional Determinants of Earnings Response Coefficients." *Journal of Accounting and Economics* 11, no. 2–3: 143–181.

Costello, A. M. 2013. "Mitigating Incentive Conflicts in Inter-Firm Relationships: Evidence From Long-Term Supply Contracts." *Journal of Accounting and Economics* 56, no. 1: 19–39.

Covitz, D. M., and P. Harrison. 2004. "Testing Conflicts of Interest at Bond Rating Agencies With Market Anticipation: Evidence That Reputation Incentives Dominate." Finance and Economics Discussion Series (2003-68).

Dai, Y., X. Li, D. Liu, and J. Lu. 2021. "Throwing Good Money After Bad: Zombie Lending and the Supply Chain Contagion of Firm Exit." *Journal of Economic Behavior & Organization* 189: 379–402.

DeHaan, E., T. Shevlin, and J. Thornock. 2015. "Market (in) Attention and the Strategic Scheduling and Timing of Earnings Announcements." *Journal of Accounting and Economics* 60, no. 1: 36–55.

DellaVigna, S., and J. M. Pollet. 2009. "Investor Inattention and Friday Earnings Announcements." *Journal of Finance* 64, no. 2: 709–749.

Dhaliwal, D., J. S. Judd, M. Serfling, and S. Shaikh. 2016. "Customer Concentration Risk and the Cost of Equity Capital." *Journal of Accounting and Economics* 61, no. 1: 23–48.

Dhaliwal, D. S., and S. S. Reynolds. 1994. "The Effect of the Default Risk of Debt on the Earnings Response Coefficient." *Accounting Review* 69: 412–419.

Dichev, I. D., and J. D. Piotroski. 2001. "The Long-Run Stock Returns Following Bond Ratings Changes." *Journal of Finance* 56, no. 1: 173–203.

Farrell, J., and P. Klemperer. 2007. "Coordination and Lock-In: Competition With Switching Costs and Network Effects." *Handbook of Industrial Organization* 3: 1967–2072.

FASB. 2022. "Accounting Standards Update (ASU) no. 2022-04." Accounting Standards Codification (4).

Files, R., and U. G. Gurun. 2018. "Lenders' Response to Peer and Customer Restatements." *Contemporary Accounting Research* 35, no. 1: 464–493.

Givoly, D., and J. Lakonishok. 1984. "Properties of Analysts' Forecasts of Earnings: A Review and Analysis of the Research." *Journal of Accounting Literature* 3, no. 1: 117–152.

Goh, J. C., and L. H. Ederington. 1993. "Is a Bond Rating Downgrade Bad News, Good News, or No News for Stockholders?" *Journal of Finance* 48, no. 5: 2001–2008.

Gompers, P., J. Ishii, and A. Metrick. 2003. "Corporate Governance and Equity Prices." *Quarterly Journal of Economics* 118, no. 1: 107–156.

Gounopoulos, D., and H. Pham. 2017. "Credit Ratings and Earnings Management Around IPOs." *Journal of Business Finance & Accounting* 44, no. 1–2: 154–195.

Grossman, S. J., and O. D. Hart. 1986. "The Costs and Benefits of Ownership: A Theory of Vertical and Lateral Integration." *Journal of Political Economy* 94, no. 4: 691–719.

Grove, S., A. Nelson, E. D. V. Calderon, and K. E. Dow. 2024. "Words to Use With Care? CEO Dispositional Optimism vs Overconfidence." *Finance Research Letters* 59: 104785.

Guan, Y., M. Wong, and Y. Zhang. 2015. "Analyst Following Along the Supply Chain." *Review of Accounting Studies* 20, no. 1: 210–241.

Gulen, H., and M. Ion. 2016. "Policy Uncertainty and Corporate Investment." *Review of Financial Studies* 29, no. 3: 523–564.

Hasan, M. M., A. Habib, and R. Zhao. 2022. "Corporate Reputation Risk and Cash Holdings." *Accounting and Finance* 62, no. 1: 667–707.

Hasan, M. M., G. J. Lobo, and B. Qiu. 2021. "Organizational Capital, Corporate Tax Avoidance, and Firm Value." *Journal of Corporate Finance* 70: 102050.

Hertzel, M. G., Z. Li, M. S. Officer, and K. J. Rodgers. 2008. "Inter-Firm Linkages and the Wealth Effects of Financial Distress Along the Supply Chain." *Journal of Financial Economics* 87, no. 2: 374–387.

Hsiao, H.-Y., W.-P. Liu, and S.-J. Wu. 2024. "Does Increased Monitoring Enhance the Credibility of Financial Reports? Evidence of Auditing Semi-Annual Financial Statements." *Accounting and Finance* 65: 753–772.

Itzkowitz, J. 2013. "Customers and Cash: How Relationships Affect Suppliers' Cash Holdings." *Journal of Corporate Finance* 19: 159–180.

Kale, J. R., and H. Shahrur. 2007. "Corporate Capital Structure and the Characteristics of Suppliers and Customers." *Journal of Financial Economics* 83, no. 2: 321–365.

Kang, M. 2022. "Credit Rating Downgrade Risk and Acquisition Decisions." *Journal of Business Finance & Accounting* 49, no. 5–6: 1011–1073.

Kaplan, S. N., and L. Zingales. 1997. "Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints?" *Quarterly Journal of Economics* 112, no. 1: 169–215.

Kim, J.-B., B. Y. Song, and Y. Zhang. 2015. "Earnings Performance of Major Customers and Bank Loan Contracting With Suppliers." *Journal of Banking & Finance* 59: 384–398.

Kolay, M., M. Lemmon, and E. Tashjian. 2016. "Spreading the Misery? Sources of Bankruptcy Spillover in the Supply Chain." *Journal of Financial and Quantitative Analysis* 51, no. 6: 1955–1990.

Lambert, D. M., and M. C. Cooper. 2000. "Issues in Supply Chain Management." *Industrial Marketing Management* 29, no. 1: 65–83.

Lee, S. M., P. Jiraporn, and H. Song. 2020. "Customer Concentration and Stock Price Crash Risk." *Journal of Business Research* 110: 327–346.

Lewbel, A. 2012. "Using Heteroscedasticity to Identify and Estimate Mismeasured and Endogenous Regressor Models." *Journal of Business & Economic Statistics* 30, no. 1: 67–80.

Li, J., J. J. Wang, and M. Yu. 2023. "Government Provided Rating, Alleviation of Financial Constraints, and Corporate Investment." *Accounting and Finance* 63, no. 4: 3763–3779.

Lian, Y. 2017. "Financial Distress and Customer–Supplier Relationships." *Journal of Corporate Finance* 43: 397–406.

Lu, G., and G. Shang. 2017. "Impact of Supply Base Structural Complexity on Financial Performance: Roles of Visible and Not-So-Visible Characteristics." *Journal of Operations Management* 53: 23–44.

Luo, S., and N. J. Nagarajan. 2015. "Information Complementarities and Supply Chain Analysts." *Accounting Review* 90, no. 5: 1995–2029.

Madsen, J. 2017. "Anticipated Earnings Announcements and the Customer–Supplier Anomaly." *Journal of Accounting Research* 55, no. 3: 709–741.

Merton, R. C. 1974. "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." *Journal of Finance* 29, no. 2: 449–470.

Modi, S. B., and S. Mishra. 2011. "What Drives Financial Performance–Resource Efficiency or Resource Slack?: Evidence From U.S. Based Manufacturing Firms From 1991 to 2006." *Journal of Operations Management* 29, no. 3: 254–273.

Nelson, A., and S. Wang. 2024. "The Importance of Cybersecurity Disclosures in Customer Relationships." *Journal of Corporate Accounting and Finance* 35, no. 3: 66–74.

Odders-White, E. R., and M. J. Ready. 2006. "Credit Ratings and Stock Liquidity." *Review of Financial Studies* 19, no. 1: 119–157.

Olsen, C., and J. R. Dietrich. 1985. "Vertical Information Transfers: The Association Between Retailers' Sales Announcements and Suppliers' Security Returns." *Journal of Accounting Research* 23: 144–166.

Opler, T., L. Pinkowitz, R. Stulz, and R. Williamson. 1999. "The Determinants and Implications of Corporate Cash Holdings." *Journal of Financial Economics* 52, no. 1: 3–46.

Patatoukas, P. N. 2012. "Customer-Base Concentration: Implications for Firm Performance and Capital Markets." *Accounting Review* 87, no. 2: 363–392.

Radhakrishnan, S., Z. Wang, and Y. Zhang. 2014. "Customers' Capital Market Information Quality and Suppliers' Performance." *Production and Operations Management* 23, no. 10: 1690–1705.

Raman, K., and H. Shahrur. 2008. "Relationship-Specific Investments and Earnings Management: Evidence on Corporate Suppliers and Customers." *Accounting Review* 83, no. 4: 1041–1081.

Shipman, J. E., Q. T. Swanquist, and R. L. Whited. 2017. "Propensity Score Matching in Accounting Research." *Accounting Review* 92, no. 1: 213–244.

Titman, S., and R. Wessels. 1988. "The Determinants of Capital Structure Choice." *Journal of Finance* 43, no. 1: 1–19.

Zhang, X. F. 2006. "Information Uncertainty and Analyst Forecast Behavior." *Contemporary Accounting Research* 23, no. 2: 565–590.

Appendix A

List of Key Variables

Variable	Definition
CAR[0,2]	The raw buy-and-hold return over the [0,2] window less the market-value-weighted returns
SUE	Earnings surprise, calculated as the difference between reported earnings per share (EPS) and the average of EPS estimates of analysts scaled by the end-of-quarter stock price
Customer Downgrade	An indicator set to one if the customer credit rating is less than its rating 6 months before
Size	Natural logarithm of total assets
MTB	Market to book ratio
Friday	An indicator variable set to one if earnings are announced on Friday
ReportingLag	Number of days between the earnings announcement date and fiscal quarter-end date
NumAnalyst	Number of analysts covering the firm during this fiscal year
Qtr4	An indicator variable set to one if it is the fourth quarter earnings announcement
Customer Size	Natural logarithm of customer total assets
Leverage	Current debt plus long-term debt divided by total assets
Cash	Cash holdings divided by total assets
SaleGrowth	The logged difference in sale between current and previous year