Abstract

This research investigates the effect of customer concentration on credit ratings. I find that credit rating agencies consider customer concentration a risk and incorporate the risk factor into their credit rating process. Firms with a higher customer concentration base are likely to get lower credit ratings. The impact of losing a major customer is severe for firms with concentrated customer bases. These firms are more likely to suffer from decreasing cash flow due to losing a major customer. I also examine several possible factors that could impact the relationship. Overall, my finding suggests that customer concentration is an essential factor when credit rating agencies assess the creditworthiness of a firm.

Customer concentration, Disclosure decisions, and Credit Ratings

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1. Introduction

This study examines whether credit rating agencies incorporate customer concentration as a business risk and incorporate such risk into their credit rating opinions. Regulators have considered the reliance on major customers as a potential business risk. Statement of Financial Accounting Standards (SFAS) 131 requires the company to disclose the number of sales from a single customer if that amount is 10 percent or more of the company's revenue. Firms face the risk of a substantial drop in cash flow when the sales to the major customer drop or when their major customer goes bankrupt (Dhaliwal et al., 2019). Since credit rating agencies provide the opinion to the bond issuers, the potential threat of losing substantial cash flow should be an important risk factor when evaluating the creditworthiness of bond issuers. Thus, I expect firms with higher customer concentration to receive lower credit ratings.

The idea that credit rating agencies take a concentrated customer base as a risk is intuitive. When a firm relies on a small number of customers, losing any customers may significantly decrease future cash flow since a small number of customers dominates the firm's future cash flow. Take Mattel for example. When Toys' R' Us filed for bankruptcy in 2017, Moody's downgraded Mattel's rating by four-level. The sales to Toys' R' US account for about 20 percent of the total revenue of Mattel, and Toys 'R' US still owes Mattel more than $135 million. Besides, after the bankruptcy of Toys' R' US, Mattel had difficulties in selling its products to other customers

(Korosec 2018). The Mattel example shows that losing a major customer when a firm relies heavily on a single customer is a significant business risk. Suppliers risk losing a large portion of future sales if the major customer declares bankruptcy or switches to another supplier. The supplier also risks losing a significant part of the anticipated future cash flow. Besides, since suppliers tend to invest in relationship-specific assets, finding another customer to utilize those assets in a short time can be challenging.

While the above arguments suggest that a concentrated customer base can be risky, keeping a few customers enables suppliers to reduce their operating costs through collaboration. Suppliers with concentrated customer bases achieve better efficiencies through mutual collaboration on marketing and advertising efforts and more effective selling expenditures (Cowley, 1988; Kalwani & Narayandas, 1995). Suppliers enjoy less selling, general and administrative expense, holding lower inventory, shorter inventory holding period, and lower inventory write down. (Ak & Patatoukas, 2016; Patatoukas, 2012). Lowering the number of customers enables suppliers to reduce demand uncertainty through Just-In-Time manufacturing and Collaborative Planning, Forecasting, and Replenishment (CPFR), reducing the uncertainty of future demand. Credit rating agencies are more likely to predict a firm's future cash flow with less uncertainty.

The above discussion suggests that a concentrated customer base increases business risks (Dhaliwal et al. 2016) but also benefits the firm (Patatoukas, 2012). However, whether such risk

or benefit is incorporated in credit ratings is unclear. To test the relation between customer concentration and credit ratings, I create four measures that capture the characteristics of customer concentration over the years 1989 – 2016. I follow Patatoukas' (2012) measure of customer concentration (CC), the rank of CC, sales to the major customer, and total sales to customers reported on the segment report to test my hypothesis. I gather my main data from Compustat Segment Data and Compustat/S&P long-term issuer-level credit rating database.

My empirical results show that customer concentration is negatively related to the supplier's credit rating. I find evidence that risks associated with a concentrated customer base result in lower supplier credit ratings. The results show that firms with a concentrated customer base are associated with lower credit ratings. In addition, I conduct a series of additional tests to support the effect of customer concentration on credit ratings. Specifically, I examine whether the impact of a concentrated customer base on credit ratings is more pronounced when suppliers invest less in R&D expenses. I also test whether these firms get lower credit ratings when they invest heavily in relationship-specific assets. My additional tests show little evidence of the effect of innovation and relationship-specific assets.

I also use instrumental variable regression to address the potential endogeneity problem by using the lagged industry average of each customer concentration measure as an instrument

variable. The results confirm that a supplier with a more concentrated customer base is associated with a lower credit rating.

My research contributes to the literature on credit ratings and customer concentration in several ways. Previous research on credit ratings mainly focuses on the accounting-based ratio (Blume et al., 1998; Kaplan & Urwitz, 1979), earning quality (Alissa et al., 2013), and managerial ability (Bonsall et al., 2016; Cornaggia et al., 2017). Some literature talks about credit ratings and the information along the supply chain. For example, Alldredge et al. (2019) find that suppliers experience negative abnormal returns during the announcement of a customer's rating downgrade. Huang and Ren (2016) document that a supplier's bankruptcy risk is positively associated with its major customer's bankruptcy risk. However, the impact of customer centration on credit ratings is ignored. This is the first paper to document the association between customer concentration and credit ratings. I extend the literature by incorporating customer concentration as a risk factor in credit rating assessments.

Second, this research contributes to the research on the informativeness of the disclosure of customer information. I find that credit rating agencies incorporate customer concentration as a business risk when making rating decisions. These findings are important because they point out that debt markets care about the firm's fundamentals and its customers' structure. Third, my results also show credit rating agencies' views on customer-supplier relationships. Although previous

studies suggest customer concentration may benefit supplies by collaborating and thus reduce the uncertainty of future cash flow, credit rating agencies consider customer concentration a business risk because firms may suffer from substantial loss when losing a major customer.

Section 2 provides the background and literature review. Section 3 shows hypothesis development. Section 4 shows the research design and sample selection. Section 5 is the result and my additional tests, and section 6 concludes.

2. Literature Review

2.1 Customer Concentration

Customer concentration is defined as the relative sales volume of customers that adds to a firm's revenue. Customer concentration captures whether the supplier works with many customers or a few customers. When a firm's revenue is primarily contributed by its major customers, it has a high customer concentration. While some level of customer concentration benefits supplier firms, the optimal level of concentration is determined by the efficiency gain and disruption risk (Cen & Dasgupta, 2021).

2.1.1 Efficiency gain and customer concentration

In operation management, limited numbers of major customers enable suppliers to collaborate with customers and supply-chain to reduce costs and increase efficiency (Ak & Patatoukas, 2016). Patatoukas (2012) finds that suppliers with concentrated customers have a higher return on assets and lower selling, general and administrative costs. Cen et al. (2016) show that firms that have a long-term relationship with customers are likely to enjoy lower loan spreads and looser covenants on the bank loan, while Campello and Gao (2017) find the firms with concentrated customer bases have higher interest rate spread and more number of restrictive covenants in new or renegotiated bank loans. A small number of customers also benefit supplier firms. Supplier firms with

concentrated customer bases generally enjoy lower advertising and marketing expenses because they have less need to attract new customers. Such suppliers tend to spend money to keep current customers and try their best to nurture long-term relationships with their major customers. Besides, a small bunch of customers enable suppliers to increase operating efficiency, such as improving inventory management (Ak and Patatoukas 2016). In sum, suppliers with concentrated customer base enjoy better operating efficiency by reducing costs and optimizing inventory management.

2.1.2 Disruption risk and customer concentration

Suppliers with few customers will likely get into problems if they lose customers. When a supplier loses a major customer, finding another customer to fill the capacity quickly is hard because these firms generally invest in relationship-specific investments customized for a specific customer. Therefore, any disruption along the supply chain could significantly impact the supplier's operating and financial performance. The problem is more serious when the supplier engages in more relationship-specific investments since switching costs are high.

Several types of disruption could cause severe damage to the supplier. One example is a bankruptcy filing. Hertzel et al. (2008) find that the pre-filing and filing date contagion effect on the stock return of suppliers is negative only for the dependent suppliers. The contagion effect is stronger when other firms within the customer's industry are also affected. Their results are

consistent with the switching cost argument. When the whole industry in the customer is affected during the pre-filing and filing period, the switching cost for the supplier to find another customer to replace major customers is high. Kolay et al. (2016) find that when the customer files Chapter 11 filings, suppliers show higher operating costs and lower profit margins in the following year of the filings.

Dhaliwal et al. (2016) argue that a concentrated customer base is a business risk because firms risk losing substantial sales and anticipated cash flow if they lose a major customer, or the major customer goes bankrupt. Dhaliwal et al.(2019) also suggest that financial distress firms with concentrated customer bases are likely to receive going concern opinions.

2.1.3 Buyer's bargaining power along the supply chain

The traditional view on customer concentration suggests buyer bargain power exists when suppliers rely on few customers. Suppliers tend to invest in relationship-specific investments to fulfill the needs of their major customers. The switching cost is high for suppliers with few customers because the relationship-specific investments are mostly designed for a specific customer. It is hard to switch the investment to another customer (Joskow, 1987). Besides, the outcome is uncertain when suppliers decide to make relationship-specific investments. Suppliers can increase their investment efficiency by getting information from customers (Dou et al., 2013).

However, customers do not have any contracts on the production capacity or price when a supplier decides to make such investments (Taylor & Plambeck, 2007). Since the supplier can hardly find an alternative use for such investment, the customer has greater bargaining power when the supplier makes a lot of relationship-specific investments. Thus, major customers can push suppliers to lower prices and extend the payment period (Gosman and Kohlbeck, 2009). Scherer and Ross (1990) argue that suppliers may fear heavy losses if the major customer changes its supplier. The fear gives customers strong bargaining power over price.

2.2 Credit Ratings

2.2.1 What is Credit Rating

Credit ratings are forward-looking opinions about the ability and willingness of debt issuers to meet their financial obligations on time and in full (S&P, 2022). Such ratings are issued by credit rating agencies. Credit ratings express relative, not absolute, opinions about an issuer's creditworthiness. A credit rating consists of a letter rating and commentary (if applicable). Letter ratings range from AAA (or equivalent) to D for an overview of the rating level, with AAA being the highest rating (See Table 1 for the overview of the rating level and the numerical value assignments used in this paper).

2.2.1 How Credit Rating is determined.

Credit rating agencies assess the firm's creditworthiness based on the firm's several factors and risks. Credit rating agencies use mathematical models to analyze quantitative data. Some small agencies rely heavily on quantitative analysis to cover virtually all issuers on the market. Larger agencies use a mix of quantitative and qualitative analysis to evaluate a firm's creditworthiness. Analysts obtain information from public sources and interview the issuer's managers. Credit rating agencies may include private information to assess a firm's creditworthiness. For example, firms may not release information that would be useful for their competitors. Analysts use the information they obtain to assess a firm's credit risk and issue their opinions. Take Standard& Poor (S&P) as an example. In S&P's corporate rating framework, S&P first assesses a firm's business risks and financial risks to determine the anchor. Business risks include country risk, industry risk, and competitive position. Financial risks are determined by a firm's cash flow/leverage. After the anchor is determined, they add several additional factors, such as capital structure and liquidity, to modify the anchor. Those modifiers could raise or lower the anchor by one or more notches. The last step is comparable rating analysis, which may raise or lower the anchor by one notch based on a holistic view of the company's credit characteristics. (S&P, 2021)

Previous research documents the association between credit ratings and accounting figures (Blume et al., 1998; Kaplan & Urwitz, 1979). Credit rating agencies rely heavily on the account fundamental figures. Recent research also shows that credit rating agencies adjust their rating

before account fraud (Huang et al. 2019). They argue that credit rating agencies adjust their ratings before accounting fraud is detected because of the private information they have. Alissa et al. (2013) find that firms use earning management to influence their credit ratings. Bonsall et al. (2016) and Cornaggia et al. (2017) find that CEO ability is associated with higher credit ratings. They argue that managerial ability is an important factor for credit rating agencies when assessing a firm's credit risk.

2.2.2 Why do issuers seek credit rating? Who uses credit ratings?

Credit ratings represent rating agencies' assessment of a firm's long-term credit risk. Rating agencies gather information, analyze, and evaluate the information, and thereby provide their opinion of the firm's creditworthiness. The rating agencies serve as intermediaries to reduce the information asymmetry between companies and capital providers (Beaver et al., 2006). Corporations sometimes decide to borrow money directly from the market by issuing bonds. Without rating agencies, it is hard for the firm to get capital from the debt market. Issuers use credit ratings to provide independent views of the issuer's creditworthiness and default risk. Millon and Thakor (1985) argue that credit rating agencies act as "screening agents." Credit rating agencies help issuers communicate the relative credit quality of their firm's debt issues. Credit ratings also help issuers decide the interest rate offer on their new debt issues. An issuer with a lower credit

rating tends to pay higher interest rates to offset the default risk investors assume. Kisgen (2006) argues that ratings signal overall firm quality. In the extreme case, firms within the same category group would be assessed with similar default probabilities.

Investors use ratings to screen whether their current investment matches their risk tolerance. While equity analysts are more interested in a firm's future profitability for the shareholder's benefit, credit rating agencies are more concerned with whether firms can pay the principal and the interest related to the debt securities the firms issue. Therefore, equity analysts are interested in upside and downside information, while credit rating agencies are more concerned with the downside information of the debt issuer (Bonsall et al., 2016). Although there are several similarities between credit rating agencies and equity analysts, credit rating agencies may put different weights on certain factors or even ignore some factors in their rating models.

2.3 Disclosure

Accounting information plays two major roles in the market. It allows users to evaluate the potential return on investment and monitor a firm's performance. Managers generally have better information about the firm's current and future profitability than outsiders. Without proper disclosure of a firm's performance and private information, such information asymmetry makes investors difficult to distinguish good firms from bad ones. Therefore, investors will value all firms

at an average level. In the worst case, The capital markets will not function properly under such information asymmetry (Akerlof, 1970). Disclosure is one way managers use to communicate with investors. In order to distinguish itself from other companies, a firm will disclose all its private information. However, private information from disclosure comes with some costs. For example, disclosing cost and profit information may attract potential rivals to join the industry. The disclosure provides rivals with information about the industry, thus increasing the competition in the industry. Therefore, managers face cost-and-benefit decisions when deciding whether to disclose private information. On the one hand, proper disclosure informs the capital markets that the firm is superior to other firms, thus reducing the cost of capital. On the other hand, proprietary costs make the disclosure undesirable since such disclosure attracts rivals' attention. Previous literature provides an extensive discussion of this conflict. e.g., see Verrecchia (2001), Dye (2001), Healy and Palepu (2001), Beyer et al. (2010).

2.3.1 Disclosure and Supply-Chain Relationship

Disclosing information on customers enhances investors' impression of the firm. Building a relationship with a well-known and well-established company increase the general public's impression. The disclosure of customers signals to the market that the firm is superior to other firms in the same industry. Johnson et al. (2010) show that IPO firms that have relationships with

large customers enjoy higher valuations and better long-term performance. Knowing customers' identity also helps investors evaluate the revenue and value of a firm by using information from the major customers (Olsen & Dietrich, 1985; Pandit et al., 2011).

Suppliers may use disclosure to retain their customers. Raman and Shahrur (2008) show that firms are likely to manipulate their earnings to maintain the stability of their relationships with customers. Cen et al. (2017) find that firms strategically disclose litigation contingencies. They find that suppliers tend to disclose favorable news timely but postpone bad news to avoid relationship termination with the customer.

3. Hypotheses Development

I expect customer concentration to influence a supplier's credit rating in the following way. First, a firm's credit rating is determined by the probability distribution of future cash flow to bondholders (Ashbaugh-Skaife et al., 2006). Credit rating agencies assess a firm's ability to pay interest and principal payments. A supplier's future cash flow is determined by its customers. When a supplier loses one customer, the future cash flow of the supplier drops. Therefore, the supplier is more likely to suffer from cash deficiency and may not pay its debt and interest on time. This could be a more serious problem if the supplier relies on a few customers. Dhaliwal et al. (2016) suggest that firms with a more concentrated customer base are likely to have a higher cost of equity. These firms are more likely to have a considerable loss when they lose their major customer, or their major customer goes bankrupt. In either case, the supplier firm's cost of capital increases because it is more likely to have lower cash flow in the future. The equity market considers customer concentration a risk, therefore requiring a higher premium for the risk. Although the debt market emphasizes the firm's ability to repay while the equity market cares more about future profitability, customer concentration is a risk in the debt market since losing major customers leads to a substantial decrease in cash flow. Firms with a concentrated customer base are more likely to suffer when they lose their major customers. Credit rating agencies incorporate financial risks when assessing issuers' creditworthiness. The substantial drop in future

cash flow increases financial risk for firms with a concentrated customer base. Credit rating agencies could incorporate such factors into risk assessment and issue a lower credit rating to firms with a concentrated customer base.

Second, as discussed in the previous section, suppliers often engage in relationship-specific investments. These investments, such as machines and equipment, are mostly customized for one specific customer. When the supplier loses a major customer, transferring the capacity to other customers is hard since relationship-specific investments are mostly designed for a specific customer. The investments specifically devoted to a customer may become unproductive, reducing the supplier's future cash flow. This will, in turn, lead to higher default risk due to lower future cash flow. Losing a major customer will cause a significant drop in cash flow for suppliers with a concentrated customer base. Besides, the supplier is unlikely to find a compatible customer. Since the credit rating agencies assess the firm's ability to repay its debt, the risk of a significant drop in future cash flow will likely increase the supplier firm's default risk, leading to a lower credit rating.

On the contrary, one can argue that suppliers with concentrated customer bases may get higher credit ratings because suppliers benefit from the customer-supplier relationship. Patatoukas (2012) shows that suppliers with a concentrated customer base enjoy lower selling, general, and administrative costs, increasing future cash flow. Such suppliers tend to spend money to nurture long-term relationships with their current customers. A steady relationship between supplier and

customer provides steady future cash flow. In this case, the supplier with a concentrated customer base will likely have a higher credit rating because the steady future cash flow decreases the likelihood of default.

To examine the effect of customer concentration on the supplier's credit rating, I test the following hypothesis:

H1: There is no association between credit ratings and customer concentration.

Next, I explore what factors mitigate the effects of customer concentration on credit ratings. Innovation is a crucial factor for suppliers. Audretsch (1995) and Cefis and Marsili (2006) show that innovation is positively and significantly related to the probability of firms' survival. Knowledge spillover from customers creates mutual dependence and less competition between customers and suppliers (Feldman, 1999). Besides, customers tend to rely on innovative suppliers since the cost of switching suppliers can be quite high. On the other hand, less innovative suppliers face fierce competition since customers can easily find another supplier. Thus, the second hypothesis is stated as follows:

H2: The effect of customer concentration on credit ratings is less pronounced for suppliers with a higher level of innovation.

Suppliers invest in relationship-specific assets to fulfill the special needs of specific customers. Such investments have very low value when the supplier loses its major customer because these assets have little alternative use. When a supplier engages in more relationship-specific assets, the cost of switching customers is relatively high. Thus, when a supplier loses a major customer, the drop in future cash flow may be more significant for suppliers who engage in many relationship-specific assets. I present the following hypothesis to examine whether the effect of customer concentration on credit ratings is more substantial when the supplier invests more in relationship-specific assets.

H3: The effect of customer concentration on credit rating is more pronounced for suppliers with a higher level of relationship-specific assets.

4. Research Design and Sample Selection

4.1 Sample Selection

My initial sample includes the firms' credit ratings. I obtained the credit ratings information from Compustat. In this paper, the ratings I use are Standard & Poor's long-term credit ratings. These ratings focus on the firm's ability to meet its long-term financial commitment. S&P long-term credit ratings assign a letter grade to issuers ranging from AAA to D. Following the previous literature, I transform the letter grades into numerical ratings from 1 (D) to 22 (AAA). I only keep one observation for every firm-year. I keep the observations that are four months after the firm's fiscal end.

The data used to calculate my measures of customer concentration are obtained from the Compustat Segment file. SFAS 14 and SFAS 131 require firms to disclose the names of the customers whose sales are more than 10% of total sales. Some firms also voluntarily disclose information about customers that are less than 10% of sales. Some firms fail to disclose the name of the customer. These firms only disclose the sales figures but leave a blank, or simply "Company A" in the column of customer names.

For control variables, I obtain INSTOWN from Thomson Reuters Institutional (13f) holding data, and NUMEST data are from I/B/E/S. STDRET is computed from CRSP. The rest of the control variables and financial information are from Compustat and CRSP.

Table 2 summarizes my sample selection. My sample period is from 1989 to 2016. My sample begins with Compustat/S&P long-term issuer-level credit rating database. I only keep one observation for every firm-year. I keep the observation that is four months after the fiscal end. Next, using Compustat Segment data, I calculate the required CC measure using the measure from Patatoukas (2012). I merge the data with Compustat, I/B/E/S, and CRSP to get the financial data, analyst following and institutional holding data, and stock return data, respectively. I winsorize all continuous variables at the top and bottom 1 percent.

4.2 Measure of Customer Concentration

To capture the extent to which a supplier's customer base is concentrated, I follow Patatoukas (2012) to create my first measure of customer concentration using the following formula:

$$CC_{it} = \sum_{j=1}^{J} \left(\frac{Sales_{ijt}}{Sales_{it}} \right)^2 ijt$$

Where $Sales_{ijt}$ represents the firm's sales to a customer j in year t and $Sales_{it}$ represents total sales for firm i in year t. The measure CC captures two elements of customer concentration: the number of major customers with which the firm interacts and the relative importance of each major customer in the firm's annual sales. CC ranges from 0 to 1, with a higher value indicating suppliers with more concentrated customer bases and *vice versa*.

The second measure I use to measure customer concentration is the rank of CC, which is ranked from 0 to 1. Following Dhaliwal et al. (2019), my third measure is MAJORSALE, which is defined as the percentage of sales contributed by the largest major customer. The fourth measure, TOTSALE, is the percentage of sales contributed by all customers that report on Compustat Segment Data.

4.3 Regression model

To test my hypothesis, I follow the model proposed by Bonsall et al.(2016):

$$Rating_{it} = \beta_0 + \beta_1 CCmeasure_{it} + \beta_2 SIZE_{it} + \beta_3 CINTENSITY_{it} + \beta_4 LEV_{it} + \beta_5 SUBORD_{it} + \beta_6 INSTOWN_{it} + \beta_7 NUMEST_{it} + \beta_8 ROA_{it} + \beta_9 LOSS_{it} + \beta_{10} INTCOV_{it} + \beta_{11} STDRET_{it} + Credit\ ratings\ Controls + Year_Fixed_Effects + Industry_Fixed_Effect + \varepsilon \quad (1)$$

Following Bonsall et al. (2016), I include the size of the supplier (SIZE), capital intensity (CINTENSITY), firm's level of debt (LEV), whether a firm has differential debt holder claims on their assets (SUBORD), percentage of institutional holdings (INSTOWN), analyst following (NUMEST), firm's performance (ROA, LOSS, INTCOV), and an equity market measure as the quality of firm's earning (STDRET). I also added several credit-ratings-related control variables. Following Alp (2013), I include two bankruptcy scores, Altman_Z and Shumway, in the regression

model. I also include CASH, dividend payer (DVP), retained earnings (RE), Tangibility, idiosyncratic and systematic risk (Idio and Systemr) in the model. To control for heterogeneity, I include year-fixed effect and industry-fixed effect.

To test *H2*, I first construct the variable R&D intensity to capture the innovation level of the supplier. The variable is defined as total R&D expense divided by total assets. I add an interaction variable, CC*RD, to check whether innovative suppliers get higher credit ratings when they have concentrated customer bases.

To test *H3*, I first construct the measure of relationship-specific assets, RSA, defined as total R&D expense multiplied by the length of the relationship. I add an interaction variable, CC*RSA, to check whether suppliers with higher RSA get lower credit ratings when they have concentrated customer bases.

5. Results

5.1 Descriptive statistics

Table 3 provides descriptive statistics for my sample. The mean of my main measure, CC, is 0.1195, which is similar to previous research. On average, a firm's largest customer provides 19% of revenue to my sample firm, while all major customers provide 44% of revenue to my sample firm. The average long-term rating is 12.72, which is around a BBB- rating on the S&P rating scale. The average debt-to-asset ratio is 28%, which is moderate. The average ROA is 0.039. On average, there are 11.11 analysts following my sample firm, while the median is only 10, which suggests that it is skewed. Finally, on average, my sample firms incur losses in 20.21% of the sample year.

Table 4 shows the correlation among variables. Credit ratings are negatively correlated with my four measures. RATING is positively correlated with SIZE, INVCOV, ROA, and NUMEST and negatively correlated with Loss and Stdret. Note that my four measures of customer concentration are highly correlated, suggesting that my four measures capture similar characteristics across my sample.

5.2 Empirical results

This section explores whether customer concentration is associated with credit ratings. To assess the impact of customer concentration on credit ratings, I estimate Equation (1) using my full sample. Table 5 shows my main result using linear regression, controlled by year- and industry-fixed effect, and cluster by firms. Column (1) to Column (4) report the results from my baseline regression with my four main measures: CC, RANK, MAJORSALE, and TOTSALE. Consistent with my prediction, the results presented in all four columns show negative and significant coefficients on all measures of customer concentration. In Column (1), CC is negatively and significantly related to credit ratings, suggesting that a firm gets a lower credit rating when its customer base is concentrated. Column (2) shows the results with the rank of CC. Results from Column (2) suggest that firms with a lower rank of CC get lower credit ratings in my sample.

In Column (3), I use MAJORSALE as my main measure of customer concentration. The results suggest that the firm gets a lower credit rating when it sells most of its goods to a single customer. In Column (4), TOTSALE is negatively and significantly related to credit ratings. The result is similar to Column (4), suggesting that a firm gets a lower credit rating when it sells most of its goods to a few customers. For control variables, SIZE, NUMEST, ROA, Altman_Z, DVP, and PROFIT are positively and significantly related to my measures of customer concentration, while LEV, SUBORD, INSTOWN, Idio, and Systemr are negatively and significantly related to my

measures of customer concentration. The relation between credit ratings and my control variables is consistent with prior literature. Overall, my results indicate that supplier firms with a concentrated customer base get lower credit ratings. In other words, credit rating agencies consider supplier firms with a highly concentrated customer base more likely to default. The R-Square is around 0.73 across four columns.

The results in Table 5, taken together, indicate that a firm's credit rating is lower when it has a relatively concentrated customer base, suggesting the importance of customer concentration when credit rating agencies assess a supplier's credit rating.

Next, I investigate the effect of innovation. As mentioned above, innovative suppliers create mutual dependence between supplier and customer, while less innovative suppliers face competition from competitors. To measure the level of innovation, I use the supplier's research and development (R&D) expense to capture the level of innovation. I add R&D and an interaction variable, RD*CC, to the model. I expect CC to be negatively related to credit ratings, and RD*CC to be positively related to credit earnings. The regression results show a negative coefficient among my four variables of interest. All four customer concentration measures are negative and significantly related to credit ratings. RD positively correlates with credit ratings, but the results are insignificant in three of the four regressions. My major variable of interest, CC*RD, is positively related to credit ratings across four columns. However, across all four models, none of

the results are significant. Taken together, although I find a positive relationship between credit ratings and CC*RD, the results are not significant. I cannot conclude that innovative suppliers mitigate the concern of downside cashflow risk from customer concentration.

Next, I investigate whether relationship-specific assets affect the relationship between customer concentration and credit ratings. To measure relationship-specific assets, I use a measure, RSA, which is defined as the length of the relationship between the supplier and the customer multiplied by R&D expense. I also add an interaction variable, RSA*CC, to measure the additional effect of RSA on credit ratings. Table 7 shows the results. All four customer concentration measures are negative and significantly related to credit ratings. However, my major variables of interest, RSA and CC*RSA, are all not significantly related to credit ratings across four regressions. However, across all four models, none of the results are significant. Overall, I find no evidence that the effect of customer concentration on credit ratings is more pronounced for suppliers with a higher level of relationship-specific assets.

Next, I investigate whether a supplier's profitability mitigates the concern of customer concentration. My profitability measure is PROFIT, defined as a three-year average of operating income before depreciation to sales. I also add an interaction variable, Profit*CC, to measure the additional effect of supplier's profitability on credit ratings. The results are in Table 8. The results are interesting. Although all my major measures of customer concentration are still negatively

related to credit ratings, none are significant. PROFIT is positively and significantly related to credit ratings. The results here are unsurprising because the credit rating shows a firm's ability to repay its debt. Profitability is one of the main factors to see if a firm is able to pay. CC*PROFIT are all negatively related to credit ratings, with only one significant result. The negative relation between CC*PROFIT and credit ratings suggests that a profitable firm with a concentrated customer base tends to have lower credit ratings. To conclude, my results show little evidence that a firm's profitability affects the relationship between credit ratings and customer concentration.

5.3 Addressing potential endogeneity problems.

5.3.1 Instrumental variables regressions

It is possible that my model suffers from an omitted variable correlated with credit ratings and my measure of customer concentration. To address such problems, I follow Dhaliwal et al. (2016) by using lagged industry averages of each customer concentration measure as my instrumental variables. Specifically, I calculate the industry average based on the 3-digit SIC industry and year and exclude the observation in the calculation. As Dhaliwal et al. (2016) discussed, this measure should meet the relevant conditions. Panel A of Table 8 presents the first-stage results I obtained by regression CC on my instrumental variables and other control variables used in my baseline model. The high R-square suggests my results do not suffer from weak

instrument problems. The result in Panel B of Table 8 shows a negative relation between customer concentration and credit rating. Therefore, to the extent that my instruments are valid, the results suggest that suppliers with concentrated customer bases receive lower credit ratings.

5.4 Robustness Checks

The tests address the concerns that the specific industries may drive the baseline results. Prior literature suggests that utilities (SIC 4900 – 4999) and financial firms (SIC 6000 – 6999) show different characteristics. To rule out the potential bias, I follow Dhaliwal et al. (2016) by excluding utilities and financial firms. The results are similar to my results in Table 5, with all the major customer concentration measures negatively and significantly related to credit ratings.

The measure of credit rating is defined as a numerical value assigned to each firm with its relative credit ratings. I chose ordinary linear regression to test my hypothesis in this research. The advantage of ordinary linear regression is the ease of interpreting the results. One issue with the ordinary linear regression with such measures is that the results tend to skew and may generate a misleading result. To mitigate such concern, I use ordered logit regression, as Dhaliwal et al. (2020) suggested, to test my hypothesis. Untabulated results show that the results are consistent with my ordinary linear regression results. All four customer concentration measures negatively and significantly correlate with the supplier's credit rating.

6. Conclusion

This study provides evidence of the negative relationship between customer concentration and credit ratings. Credit rating agencies provide opinions on the firm's creditworthiness by assessing the firm's ability to repay debts and related interests. A firm with a concentrated customer base will likely suffer from decreasing substantial cash flow when losing a major customer; thus, the ability to repay the debt is reduced. I find that credit rating agencies take customer concentration as a risk when giving the rating to the firm. I conducted several additional tests to see what factors drive the effect. The results provide little evidence of the impact of suppliers' profitability, innovation, and relationship-specific assets. The relation holds when I exclude financial and utility firms. In sum, this research is the first to show the impact of customer concentration on credit ratings.

Appendix A – Variable Definition

Variable	Definition
RATING	S&P long-term issuer credit rating four months after firm i's fiscal year t ending date.
CC	The Herfindahl index calculated across all customers in year t.
RANK	Rank value of CC from 0 to 1
MAJORSALE	The percentage of sales contributed by the firm's largest customer in year t.
TOTSALE	The total percentage of sales contributed by all customers that comprise at least 10 percent of a firm's sales in year t.
SIZE	The natural logarithm of total assets for firm i in fiscal year t.
CINTENSITY	Gross property, plant, and equipment scaled by total assets for firm i in fiscal year t.
LEV	Total debt (long-term plus the portion of long-term debt in current liabilities) scaled by total assets for firm i in fiscal year t.
SUBORD	A binary variable set to 1 if firm i has subordinated debt in fiscal year t. Otherwise, set to 0.
INSTOWN	The average percentage of common equity shares held by institutional investors for firm i duringfiscal year t.
NUMEST	The number of earnings forecasts outstanding during the last month of a firm's fiscal year according to I/B/E/S.
ROA	Net income (before extraordinary item) scaled by total assets for firm i in fiscal year t.
LOSS	A binary variable set to 1 if firm i reports basic earnings per share (EPS) less than zero in iscal year t. Otherwise, set to 0.
INTCOV	Operating income before depreciation and interest expense divided by interest expense for firm i during fiscal year t.
STDRET	The standard deviation of fiscal year t daily stock returns for firm i.
Altman_Z	Bankruptcy score defined as 1.2(working capital / total assets) + 1.4(retained earnings / total assets) + 3.3(earnings before interest and tax / total assets) + 0.6(market value of equity / total liabilities) + 1.0(sales / total assets)
Shumway	Default probability as in Bharath and Shumway (2008)
Idio	The root-mean-square error from regression of firm's daily stock returns on the CRSP VW index return.
Systemr	Market model beta estimated from the idiosyncratic risk regression.
CASH	Cash scaled by total assets
DVP	A binary variable set to 1 if firm i has positive dividend per share.
LEV	Three-year average of long-term liability scaled by total assets.
PROFIT	Three-year average of operating income before depreciation to sales
RE	Retained earnings scaled by total assets.
Tangibility	Net property, plant, and equipment scaled by total assets.
RD	Research & development expense scaled by total assets. 0 if R&D expense is missing.
RSA	Length of relationship multiplied by research and development expense.

Tables

Table1. The Rating Scale

Rating Group	Rating	Numerical Value Assigned	Category definition
Investment Grade	AAA	22	Extremely strong capacity to meet financial commitments.
	AA	21,20,19	Very strong capacity to meet financial commitments
	A	18,17,16	Strong capacity to meet financial commitments, but somewhat susceptible to adverse economic conditions and changes in circumstances
	BBB	15,14	Adequate capacity to meet financial commitments, but more subject to adverse economic conditions
	BBB-	13	Considered lowest investment-grade by market participants
Speculative Grade	BB+	12	Considered highest speculative-grade by market participants
	BB	11,10	Less vulnerable in the near-term but faces major ongoing uncertainties to adverse business, financial and economic conditions
	B	9,8,7	More vulnerable to adverse business, financial and economic conditions but currently has the capacity to meet financial commitments
	CCC	6,5,4	Currently vulnerable and dependent on favorable business, financial and economic conditions to meet financial commitments
	CC	3	Highly vulnerable; default has not yet occurred, but is expected to be a virtual certainty
	C	2	Currently highly vulnerable to non-payment, and ultimate recovery is expected to be lower than that of higher rated obligations
Default	D	1	Payment default on a financial commitment or breach of an imputed promise; also used when a bankruptcy petition has been filed or similar action taken

Notes: This describes categories for credit ratings and the numerical scale used in this paper. Multiple numerical values for a single rating level represents the number assigned with a +, no qualifier, or a – qualifier. The source of rating definition is Standard & Poor's (2019) general summary of the opinions reflect by the ratings.

Table 2. Sample Selection

Observations available in the Compustat/S&P rating long-term rating from 1994 through 2017. Only keep the rating that is four months after the firm's fiscal end date.	58,036
Less: Merging with firms that reported segment in the Compustat Segment data file	(41,863)
Merging with Compustat	(958)
Merging with I/B/E/S	(6,053)
Merging with CRSP	(1,344)
Observation with missing data	(5,740)
Final Sample	2,078

Table 3. Descriptive Statistic

Variable	N	Mean	Std. dev	Q1	Median	Q3
RATING	2078	12.7298	3.3827	10.0000	13.0000	15.0000
CC	2078	0.1195	0.1366	0.0230	0.0754	0.1601
RANK	2078	0.5004	0.2887	0.2506	0.5004	0.7502
MAJORSALE	2078	0.1912	0.1389	0.1028	0.1600	0.2500
TOTSALE	2078	0.4422	0.2746	0.1900	0.4300	0.6585
SIZE	2078	8.1046	1.2669	7.2239	7.9966	8.8899
CINTENSITY	2078	0.4759	0.3120	0.2288	0.4004	0.6643
SUBORD	2078	0.1340	0.3408	0.0000	0.0000	0.0000
INSTOWN	2078	0.7138	0.2821	0.5606	0.7590	0.8966
INTCOV	2078	21.1890	39.1171	5.6359	9.7166	17.2311
NUMEST	2078	10.7911	7.1534	5.0000	10.0000	15.0000
STDRET	2078	0.2021	0.4017	0.0000	0.0000	0.0000
ROA	2078	0.0386	0.0913	0.0147	0.0516	0.0842
STDRET	2078	0.1091	0.0733	0.0597	0.0880	0.1329
Altman_Z	2078	3.6610	3.0810	2.2148	3.1944	4.4900
Shumway	2078	3.5454	13.2703	0.0000	0.0000	0.0094
Idio	2078	0.0213	0.0135	0.0125	0.0178	0.0260
Systemr	2078	1.0374	0.4084	0.7639	1.0032	1.2519
CASH	2078	0.1262	0.1284	0.0338	0.0852	0.1789
DVP	2078	0.5761	0.4944	0.0000	1.0000	1.0000
LEV	2078	0.2842	0.1858	0.1659	0.2591	0.3657
PROFIT	2078	0.1681	0.1331	0.1069	0.1534	0.2248
RD	2078	0.0363	0.0434	0.0062	0.0181	0.0501
RE	2078	0.1014	0.7834	0.0027	0.1897	0.3903
Tangibility	2078	0.2264	0.1519	0.1115	0.1915	0.3022

Table 4. Correlation Analysis – Pearson & Spearman

Variable	RATING	CC	RANK	MAJORSALE	TOTSALE	SIZE	CINTENSITY	SUBORD	INSTOWN	INTCOV	NUMEST	LOSS	ROA	STDRET	Altman_Z
RATING	1	0.00486	0.00844	-0.16966	-0.01729	0.63589	-0.01602	-0.2413	-0.03989	0.29699	0.47319	-0.44812	0.54933	-0.52295	0.41659
		0.86	0.7594	<.0001	0.5302	<.0001	0.5606	<.0001	0.1474	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
CC	-0.00325	1	0.83662	0.54852	0.78086	0.04395	-0.08909	0.01169	0.04291	0.0558	0.07863	-0.09173	0.07676	-0.04985	-0.02028
	0.9059		<.0001	<.0001	<.0001	0.1103	0.0012	0.6713	0.1191	0.0426	0.0042	0.0008	0.0052	0.0701	0.4614
RANK	-0.00328	1	1	0.5904	0.91365	0.04428	-0.17286	-0.01072	0.06628	0.05928	0.10103	-0.0602	0.0633	-0.05529	-0.02377
	0.9052	<.0001		<.0001	<.0001	0.1077	<.0001	0.6972	0.016	0.0312	0.0002	0.0287	0.0214	0.0445	0.388
MAJORSALE	-0.17027	0.57153	0.57153	1	0.4638	-0.11205	-0.02957	0.01332	-0.08922	-0.01353	0.00041	0.03628	-0.023	0.10153	-0.07216
	<.0001	<.0001	<.0001		<.0001	<.0001	0.2829	0.6286	0.0012	0.6231	0.9882	0.1875	0.4036	0.0002	0.0087
TOTSALE	-0.02827	0.92526	0.92526	0.46268	1	0.06189	-0.17415	0.01469	0.10165	0.03313	0.06936	-0.06104	0.03827	-0.06199	-0.04424
	0.3045	<.0001	<.0001	<.0001		0.0245	<.0001	0.5936	0.0002	0.2288	0.0117	0.0265	0.1645	0.0242	0.108
SIZE	0.63839	0.04692	0.04692	-0.11496	0.05273	1	-0.07321	-0.19086	0.11689	0.18383	0.5426	-0.25065	0.27559	-0.3756	0.15896
	<.0001	0.0883	0.0883	<.0001	0.0554		0.0078	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
CINTENSITY	0.05691	-0.2021	-0.2021	-0.10221	-0.20166	-0.05128	1	-0.09117	-0.02031	-0.06476	-0.23119	0.11355	-0.0373	0.07175	-0.04727
	0.0386	<.0001	<.0001	0.0002	<.0001	0.0624		0.0009	0.4607	0.0186	<.0001	<.0001	0.1755	0.0091	0.0859
SUBORD	-0.24753	-0.01071	-0.01069	0.02094	0.01302	-0.19844	-0.09148	1	-0.07302	-0.11988	-0.16534	0.05105	-0.09827	0.12189	-0.09639
	<.0001	0.6975	0.6979	0.447	0.6365	<.0001	0.0009		0.0079	<.0001	<.0001	0.0636	0.0003	<.0001	0.0005
INSTOWN	-0.09605	0.07526	0.07527	-0.0917	0.11195	0.08396	-0.06794	-0.06243	1	-0.03248	0.02005	-0.0099	0.0157	-0.13749	-0.11978
	0.0005	0.0062	0.0062	0.0008	<.0001	0.0023	0.0135	0.0233		0.2382	0.4666	0.7191	0.5687	<.0001	<.0001
INTCOV	0.66753	0.0716	0.07158	-0.05719	0.03162	0.39228	-0.02208	-0.27388	0.00101	1	0.2844	-0.15225	0.18864	-0.10259	0.3474
	<.0001	0.0092	0.0093	0.0377	0.2508	<.0001	0.4226	<.0001	0.9708		<.0001	<.0001	<.0001	0.0002	<.0001
NUMEST	0.48216	0.10578	0.10576	0.03506	0.07259	0.58998	-0.22007	-0.16503	0.05969	0.42265	1	-0.19803	0.24932	-0.23563	0.34452
	<.0001	0.0001	0.0001	0.2029	0.0083	<.0001	<.0001	<.0001	0.0301	<.0001		<.0001	<.0001	<.0001	<.0001
LOSS	-0.44867	-0.06017	-0.06015	0.06828	-0.05648	-0.25527	0.06348	0.05105	-0.01905	-0.3934	-0.22098	1	-0.69407	0.48032	-0.29126
	<.0001	0.0287	0.0288	0.0131	0.0401	<.0001	0.021	0.0636	0.489	<.0001	<.0001		<.0001	<.0001	<.0001
ROA	0.59769	0.08646	0.08642	0.00177	0.04125	0.2807	0.0045	-0.15597	-0.0634	0.59684	0.34562	-0.67318	1	-0.54849	0.43739
	<.0001	0.0017	0.0017	0.9487	0.134	<.0001	0.8701	<.0001	0.0212	<.0001	<.0001	<.0001		<.0001	<.0001
STDRET	-0.54151	-0.09326	-0.09324	0.08745	-0.08839	-0.43439	0.03885	0.13905	-0.06921	-0.36599	-0.31193	0.42954	-0.46654	1	-0.19622
	<.0001	0.0007	0.0007	0.0015	0.0013	<.0001	0.1581	<.0001	0.0119	<.0001	<.0001	<.0001	<.0001		<.0001
Altman_Z	0.58368	0.02787	0.02785	-0.06461	-0.00817	0.18657	-0.0244	-0.14521	-0.09801	0.63496	0.33527	-0.45992	0.67752	-0.35448	1
	<.0001	0.3114	0.3118	0.0188	0.7668	<.0001	0.3756	<.0001	0.0004	<.0001	<.0001	<.0001	<.0001	<.0001	

Table 5: Baseline Model

VARIABLES	(1) Credit rating	(2) Credit rating	(3) Credit rating	(4) Credit rating
CC	-1.738***			
	(-2.95)			
RANK		-1.095***		
		(-4.35)		
MAJORSALE			-1.645***	
			(-3.27)	
TOTSALE				-1.266***
				(-4.43)
SIZE	0.809***	0.802***	0.805***	0.805***
	(8.59)	(8.62)	(8.60)	(8.56)
CINTENSITY	0.508	0.459	0.523	0.451
	(1.14)	(1.02)	(1.17)	(1.00)
SUBORD	-0.458**	-0.450**	-0.475**	-0.449**
	(-2.45)	(-2.47)	(-2.57)	(-2.45)
INSTOWN	-0.859***	-0.901***	-0.874***	-0.897***
	(-3.12)	(-3.32)	(-3.21)	(-3.25)
INTCOV	0.001	0.001	0.001	0.001
	(0.53)	(0.59)	(0.54)	(0.55)
NUMEST	0.029**	0.030**	0.029**	0.029**
	(2.15)	(2.27)	(2.16)	(2.21)
LOSS	-0.252	-0.241	-0.244	-0.257
	(-1.47)	(-1.43)	(-1.43)	(-1.52)
ROA	3.588***	3.604***	3.626***	3.444***
	(3.58)	(3.64)	(3.63)	(3.46)
STDRET	-1.903*	-1.957*	-1.959*	-2.001**
	(-1.85)	(-1.95)	(-1.92)	(-1.99)
Altman_Z	0.122***	0.118***	0.122***	0.121***
	(3.74)	(3.67)	(3.75)	(3.70)
Shunway	-0.003	-0.003	-0.003	-0.003
	(-0.59)	(-0.53)	(-0.60)	(-0.53)
Idio	-19.694***	-19.320***	-18.954***	-19.423***
	(-2.98)	(-2.98)	(-2.88)	(-2.96)
Systemr	-0.737***	-0.728***	-0.733***	-0.719***
	(-4.79)	(-4.76)	(-4.78)	(-4.71)
CASH	-0.172	0.064	-0.048	-0.020
	(-0.24)	(0.09)	(-0.07)	(-0.03)
DVP	1.512***	1.520***	1.526***	1.508***
	(8.48)	(8.63)	(8.58)	(8.59)
LEV	-6.526***	-6.412***	-6.559***	-6.306***
	(-3.94)	(-3.90)	(-3.96)	(-3.83)
PROFIT	3.384***	3.513***	3.464***	3.436***
	(4.17)	(4.42)	(4.32)	(4.26)
RE	0.181	0.153	0.165	0.168
	(1.22)	(1.09)	(1.13)	(1.20)
Tangibility	-0.525	-0.480	-0.517	-0.486

	(-0.52)	(-0.47)	(-0.51)	(-0.48)
Observations	2,078	2,078	2,078	2,078
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Adjusted R^2	0.738	0.743	0.739	0.742

Notes: This table reports the results of linear regressions of customer concentration measures on the credit ratings of the supplier firm and a set of control variables. The dependent variable is the supplier's S&P long-term credit rating. CC is the Herfindahl index calculated across all customers reported in the firm's segment report. RANK is the rank value of CC from 0 to 1. MAJORSALE is the percentage of sales the firm's largest customer contributed in year t. TOTSALE is the total percentage of sales contributed by all customers that are reported in the firm's segment data. Other variables are defined in Appendix A. The t-statistics are reported in parentheses. Statistical significance of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Table 6: R&D intensity

VARIABLES	(1) Credit rating	(2) Credit rating	(3) Credit rating	(4) Credit rating
CC	-2.432**			
	(-3.07)			
RANK		-1.434***		
		(-4.47)		
MAJORSALE			-2.30***	
			(-3.48)	
TOTSALE				-1.703***
				(-4.61)
RD	4.985*	2.473	3.525	3.037
	(1.84)	(0.65)	(1.02)	(0.89)
CC*RD	14.610	7.754	13.419	9.652
	(1.12)	(1.46)	(1.30)	(1.53)
SIZE	0.797***	0.788***	0.792***	0.792***
	(8.56)	(8.56)	(8.56)	(8.51)
CINTENSITY	0.376	0.325	0.396	0.319
	(0.83)	(0.71)	(0.87)	(0.70)
SUBORD	-0.381**	-0.368**	-0.403**	-0.357*
	(-2.05)	(-2.03)	(-2.18)	(-1.95)
INSTOWN	-0.797***	-0.852***	-0.819***	-0.844***
	(-2.91)	(-3.14)	(-3.03)	(-3.06)
INTCOV	0.001	0.001	0.001	0.001
	(0.44)	(0.46)	(0.44)	(0.43)
NUMEST	0.024*	0.025*	0.024*	0.024*
	(1.83)	(1.87)	(1.81)	(1.84)
LOSS	-0.298*	-0.292*	-0.294*	-0.307*
	(-1.71)	(-1.70)	(-1.70)	(-1.78)
ROA	4.160***	4.291***	4.224***	4.142***
	(4.13)	(4.31)	(4.20)	(4.16)
STDRET	-2.165**	-2.244**	-2.241**	-2.283**
	(-2.12)	(-2.25)	(-2.21)	(-2.29)
Altman_Z	0.114***	0.109***	0.112***	0.111***
	(3.53)	(3.42)	(3.51)	(3.47)
Shunway	-0.003	-0.002	-0.003	-0.002
	(-0.47)	(-0.39)	(-0.50)	(-0.37)
Idio	-19.652***	-19.154***	-18.874***	-19.052***
	(-3.01)	(-2.98)	(-2.91)	(-2.92)
Systemr	-0.741***	-0.738***	-0.738***	-0.729***
	(-4.86)	(-4.86)	(-4.84)	(-4.81)
CASH	-1.036	-0.853	-0.916	-0.923
	(-1.61)	(-1.35)	(-1.43)	(-1.45)
DVP	1.547***	1.549***	1.557***	1.542***
	(8.86)	(9.02)	(8.96)	(9.01)
LEV	-6.069***	-5.860***	-6.068***	-5.759***
	(-3.61)	(-3.48)	(-3.60)	(-3.45)
PROFIT	3.138***	3.292***	3.235***	3.197***

	(3.91)	(4.26)	(4.09)	(4.06)
RE	0.209	0.187	0.197	0.198
	(1.30)	(1.21)	(1.24)	(1.30)
Tangibility	-0.075	-0.027	-0.066	-0.022
	(-0.07)	(-0.03)	(-0.06)	(-0.02)
Observations	2,078	2,078	2,078	2,078
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Adjusted R^2	0.742	0.749	0.744	0.748

Notes: This table reports the results of linear regressions of customer concentration measures on the credit ratings of the supplier firm after controlling the supplier's innovation measured by R&D intensity (RD). RD is defined as research & development expense scaled by total assets. The dependent variable is the supplier's S&P long-term credit rating. CC is the Herfindahl index calculated across all customers reported in the firm's segment report. RANK is the rank value of CC from 0 to 1. MAJORSALE is the percentage of sales the firm's largest customer contributed in year t. TOTSALE is the total percentage of sales contributed by all customers that are reported in the firm's segment data. Other variables are defined as in Appendix A. The t-statistics are reported in parentheses. Statistical significance of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Table 7: Relationship Specific Asset

VARIABLES	(1) Credit rating	(2) Credit rating	(3) Credit rating	(4) Credit rating
CC	-1.852***			
	(-3.10)			
RANK		-1.110***		
		(-4.35)		
MAJORSALE			-1.738***	
			(-3.41)	
TOTSALE				-1.330***
				(-4.71)
RSA	0.000	0.000	-0.000	0.000
	(0.47)	(0.49)	(-0.34)	(0.19)
CC*RSA	0.000	0.000	0.000	0.000
	(1.23)	(0.02)	(1.56)	(0.58)
SIZE	0.786***	0.776***	0.782***	0.781***
	(8.23)	(8.21)	(8.26)	(8.17)
CINTENSITY	0.454	0.388	0.468	0.388
	(1.02)	(0.86)	(1.04)	(0.86)
SUBORD	-0.455**	-0.450**	-0.473**	-0.447**
	(-2.45)	(-2.49)	(-2.57)	(-2.45)
INSTOWN	-0.840***	-0.878***	-0.856***	-0.878***
	(-3.05)	(-3.22)	(-3.15)	(-3.18)
INTCOV	0.001	0.001	0.001	0.001
	(0.46)	(0.48)	(0.44)	(0.47)
NUMEST	0.027**	0.028**	0.027**	0.027**
	(2.00)	(2.13)	(2.01)	(2.03)
LOSS	-0.261	-0.251	-0.253	-0.266
	(-1.53)	(-1.49)	(-1.49)	(-1.58)
ROA	3.593***	3.618***	3.625***	3.449***
	(3.58)	(3.67)	(3.63)	(3.47)
STDRET	-1.890*	-1.970*	-1.937*	-2.009**
	(-1.84)	(-1.96)	(-1.90)	(-2.00)
Altman_Z	0.125***	0.121***	0.125***	0.123***
	(3.81)	(3.71)	(3.82)	(3.75)
Shunway	-0.003	-0.003	-0.003	-0.003
	(-0.57)	(-0.49)	(-0.58)	(-0.50)
Idio	-20.130***	-19.729***	-19.393***	-19.851***
	(-3.04)	(-3.04)	(-2.95)	(-3.03)
Systemr	-0.734***	-0.722***	-0.729***	-0.715***
	(-4.78)	(-4.73)	(-4.76)	(-4.69)
CASH	-0.241	0.021	-0.125	-0.067
	(-0.34)	(0.03)	(-0.18)	(-0.10)
DVP	1.515***	1.522***	1.531***	1.509***
	(8.51)	(8.64)	(8.65)	(8.61)
LEV	-6.618***	-6.498***	-6.655***	-6.400***
	(-3.96)	(-3.93)	(-3.99)	(-3.86)
PROFIT	3.221***	3.378***	3.303***	3.270***

	(4.04)	(4.35)	(4.19)	(4.17)
RE	0.175	0.146	0.159	0.161
	(1.17)	(1.05)	(1.08)	(1.15)
Tangibility	-0.413	-0.343	-0.406	-0.361
	(-0.41)	(-0.34)	(-0.40)	(-0.35)
Observations	2,078	2,078	2,078	2,078
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Adjuested R^2	0.739	0.744	0.740	0.748

Notes: This table reports the results of linear regressions of customer concentration measures on the credit ratings of the supplier firm after control for the firm's relationship-specific assets (RSA). RSA is defined as the length of the relationship multiplied by research and development expense three-year average of operating income before depreciation to sales. The dependent variable is the supplier's S&P long-term credit rating. CC is the Herfindahl index calculated across all customers reported in the firm's segment report. RANK is the rank value of CC from 0 to 1. MAJORSALE is the percentage of sales the firm's largest customer contributed in year t. TOTSALE is the total percentage of sales contributed by all customers that are reported in the firm's segment data. Other variables are defined as in Appendix A. The t-statistics are reported in parentheses. Statistical significance of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Table 8: Profitability

VARIABLES	(1) Credit rating	(2) Credit rating	(3) Credit rating	(4) Credit rating
CC	-0.361			
	(-0.4)			
RANK		-0.485		
		(-1.15)		
MAJORSALE			-0.820	
			(-1.07)	
TOTSALE				-0.649
				(-1.28)
PROFIT	4.315***	5.879***	4.634***	4.980***
	(4.48)	(3.54)	(3.77)	(3.55)
CC*PROFIT	-8.218*	-4.550	-4.777	-3.713
	(66)	(-1.55)	(-1.22)	(-1.21)
SIZE	0.802***	0.798***	0.802***	0.804***
	(8.51)	(8.54)	(8.56)	(8.52)
CINTENSITY	0.515	0.478	0.529	0.470
	(1.15)	(1.05)	(1.18)	(1.04)
SUBORD	-0.460**	-0.446**	-0.476**	-0.451**
	(-2.46)	(-2.44)	(-2.57)	(-2.46)
INSTOWN	-0.878***	-0.908***	-0.887***	-0.904***
	(-3.19)	(-3.37)	(-3.27)	(-3.29)
INTCOV	0.001	0.001	0.001	0.001
	(0.48)	(0.61)	(0.51)	(0.52)
NUMEST	0.028**	0.029**	0.028**	0.029**
	(2.11)	(2.19)	(2.08)	(2.15)
LOSS	-0.259	-0.240	-0.247	-0.267
	(-1.52)	(-1.43)	(-1.45)	(-1.58)
ROA	3.524***	3.569***	3.620***	3.374***
	(3.52)	(3.63)	(3.63)	(3.39)
STDRET	-1.878*	-1.896*	-1.912*	-1.965*
	(-1.83)	(-1.9)	(-1.87)	(-1.96)
Altman_Z	0.124***	0.124***	0.125***	0.124***
	(3.79)	(3.89)	(3.83)	(3.78)
Shunway	-0.003	-0.003	-0.003	-0.003
	(-0.58)	(-0.55)	(-0.59)	(-0.55)
Idio	-20.084***	-19.519***	-19.356***	-19.344***
	(-3.05)	(-3.03)	(-2.96)	(-2.97)
Systemr	-0.723***	-0.720***	-0.722***	-0.714***
	(-4.67)	(-4.67)	(-4.67)	(-4.66)
CASH	-0.179	0.014	-0.051	-0.062
	(-0.25)	(0.02)	(-0.07)	(-0.09)
DVP	1.510***	1.531***	1.528***	1.502***
	(8.45)	(8.76)	(8.55)	(8.52)
LEV	-6.532***	-6.362***	-6.552***	-6.252***
	(-3.97)	(-3.91)	(-3.98)	(-3.83)
RE	0.183	0.144	0.163	0.172

	(1.26)	(1.00)	(1.11)	(1.25)
Tangibility	-0.560	-0.533	-0.551	-0.524
	(-0.55)	(-0.52)	(-0.54)	(-0.51)
Observations	2,078	2,078	2,078	2,078
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Adjuested R^2	0.739	0.744	0.740	0.743

Notes: This table reports the results of linear regressions of customer concentration measures on the credit ratings of the supplier firm after controlling for the supplier's profitability. PROFIT is defined as the three-year average of operating income before depreciation to sales. The dependent variable is the supplier's S&P long-term credit rating. CC is the Herfindahl index calculated across all customers that are reported in the firm's segment report. RANK is the rank value of CC from 0 to 1. MAJORSALE is the percentage of sales the firm's largest customer contributed in year t. TOTSALE is the total percentage of sales contributed by all customers that are reported in the firm's segment data. Other variables are defined as in Appendix A. The t-statistics are reported in parentheses. Statistical significance of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Table 9:

Panel A: Instrumental Variable – 2SLS – First Stage

First Stage

VARIABLES	(1) CC
$AVGCC_{t-2}$	0.2743***
	(0.0384)
SIZE	-0.0135***
	(0.0028)
CINTENSITY	-0.0090
	(0.0097)
LEV	0.0115
	(0.0184)
SUBORD	0.0021
	(0.0068)
INSTOWN	0.0061
	(0.0111)
INTCOV	-0.0001
	(0.0111)
NUMEST	-0.0000
	(0.0003)
LOSS	0.0051
	(0.0055)
ROA	0.0058
	(0.0302)
STDRET	0.0555
	(0.0708)
Observations	2,078
R-squared	0.1745

Panel B: Instrumental Variable – 2SLS – Second Stage

	Second Stage
VARIABLES	(1) rating
CC	-5.850***
	(2.243)
SIZE	0.736***
	(0.0702)
CINTENSITY	0.719***
	(0.173)
LEV	-3.199***
	(0.306)
SUBORD	-0.446***
	(0.122)
INSTOWN	-0.385*
	(0.213)
INTCOV	0.00688***
	(0.00253)
NUMEST	0.0389***
	(0.00893)
LOSS	-0.287***
	(0.101)
ROA	6.594***
	(0.644)
STDRET	-22.68***
	(1.173)
Observations	2,078
R-squared	0.705

Notes: This table reports results from 2-Stage Least Squares regression relating to credit rating to customer concentration measures and control variables using instrumental variables. Panel A presents first-stage results, and Panel B presents second-stage results. The dependent variable of Panel A is CC. CC is the Herfindahl index calculated across all customers that are reported in the firm's segment report. AVGCC is the average Customer HHI of firms in the supplier's 3-dight SIC industry and year. The dependent variable of Panel B is the supplier's S&P long-term credit rating. Other variables are defined as in Appendix A. The standard deviation is reported in parentheses. Statistical significance of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

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