Journal of Financial Economics 123 (2017) 108–136

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Customer concentration and loan contract terms[☆]

Murillo Campello[a,*], Janet Gao[b]

[a] Cornell University & NBER, 369 Sage Hall, 114 East Avenue, Ithaca, NY 14853-6201, United States
[b] Indiana University, 1309 E 10th Street, Bloomington, IN 47401, United States

ARTICLE INFO

Article history:
Received 4 November 2015
Revised 11 February 2016
Accepted 7 March 2016
Available online 28 September 2016

JEL Classification:
G21
G30
G32

Keywords:
Customer concentration
Bank loans
Contract terms
Financial distress
Instrumental variables

ABSTRACT

We study pricing and non-pricing features of loan contracts to gauge how the credit market evaluates a firm's customer-base profile and supply-chain relations. Higher customer concentration increases interest rate spreads and the number of restrictive covenants featured in newly initiated as well as renegotiated bank loans. Customer concentration also abbreviates the maturity of those loans as well as the relationship between firms and their banks. These effects are intensified by customers' financial distress, the level of relationship-specific investments, and the use of trade credit in customer–supplier relations. Our evidence shows that a deeper exposure to a small set of large customers bears negative consequences for a firm's relations with its creditors, revealing limits to integration along the supply chain.

1. Introduction

U.S. manufacturers attribute, on average, one-third of their sales to a small set of "large customers." A concentrated customer base is often cited as a positive factor in analyst reports, management forecasts, and even IPO prospectuses, as it is believed to increase economies of scale and improve operating efficiency. These arguments even find support in academic research (e.g., Irvine, Park, and Yildizhan, 2014; Patatoukas, 2012). Relying on large customers has shortcomings, nonetheless. Major customers demand lower prices, purchase irregularly, and often delay payments (Fee and Thomas, 2004; Kelly, Lustig, and Van Nieuwerburgh, 2013; Murfin and Njoroge, 2014).[1] They also require firms to make relationship-specific investments (Allen and Phillips, 2000; Titman and Wessels, 1988). Shocks to large firms are also known to reverberate through their supply chain (Cohen and Frazzini, 2008; Kolay, Lemmon, and Tashjian, 2016). Critically, the literature has not examined whether a close association with fewer, larger customers exposes firms to costs and risks that may ultimately affect their access to credit. This issue becomes pressing as the level of customer concentration in the makeup of supply chains in the U.S. has increased in recent years.

☆ We are thankful to Ted Fee, Erasmo Giambona, and Sudheer Chava for sharing their data. We also thank Kenneth Ahern, Kevin Aretz, Jean-Noel Barrot, Martijn Cremers, Sudipto Dasgupta, Jerry Hoberg, Tomislav Ladika, Rafael Matta, Pamela Moulton, Justin Murfin, Maureen O'Hara, Gordon Phillips, and Felipe Silva for their valuable input. Comments from seminar participants at Cornell University, McGill–HEC Montreal, Nova de Lisboa University, Tulane University, University of Notre Dame, and USC Finance, Organizations and Markets conference are also appreciated.

* Corresponding author.
E-mail addresses: campello@cornell.edu (M. Campello), janetgao@indiana.edu (J. Gao).

1 These behaviors have attracted the attention of the financial press, with reports that large, powerful firms such as Walmart and P&G "abuse" their suppliers when paying for products. See *Wall Street Journal* article: "Small firms' big customers are slow to pay" (June 6, 2012).

http://dx.doi.org/10.1016/j.jfineco.2016.03.010

This paper examines how the credit market evaluates a firm's customer base, showing how customer concentration, customer financial status, relationship investments, and various dimensions of customer–supplier relations affect a firm's creditworthiness. It does so looking at detailed data from private loan contracts between firms and their banks. The contract-level analysis we conduct is unique in allowing us to assess how informed lenders modify the terms of their credit offerings in response to the evolving nature of firms' customer base. We empirically examine the impact of customer concentration on several features of bank loans, including interest rate spreads, maturity, and the number of restrictive covenants. We also study the impact of customer concentration on the length and depth of the relationships between firms and their banks. Our results are new in revealing significant costs associated with firms' reliance on large customers. We show that these costs are manifested along various dimensions, pointing to limitations to deeper integration along the supply chain.

To perform our tests, we gather information on bank loan terms from LPC–Dealscan and merge that information with data on corporate customers from Compustat's Segment Database. Our data collection produces a comprehensive sample of 3,375 loans granted to 1,110 individual firms in the manufacturing sector over 25 years. We add to these data information on corporate failures, product differentiation, and other firm- and industry-level characteristics in order to sharpen our inferences.

Our baseline results can be summarized as follows. A more concentrated customer base generally increases both the interest rate spreads and the number of restrictive covenants featured in new (or renewed) bank loans. Customer concentration also reduces the maturity of those loans. These effects are statistically and economically significant. Controlling for bank identity, industry effects, macroeconomic conditions, and firm characteristics, a one-standard-deviation increase in customer concentration leads to 10 basis points higher interest spreads on bank loans; or a 6% higher loan markup compared to an average spread of 179 basis points. The same shift leads to 0.2 additional restrictive loan covenants; compared to the sample mean of 1.8 covenants. It also leads to a reduction in loan maturity by two months; compared to average maturity of 46 months. These magnitudes are significant given the highly competitive credit market that we study.

We also examine whether customer concentration affects the length and depth of firm-bank relations. We find that banks lend less to firms with more concentrated customer bases. Banks also abbreviate the duration of their credit relationships with those firms.

Estimates of the relation between customer concentration and borrowing terms are subject to empirical biases. In particular, one may argue that unobserved characteristics might cause a firm's customer concentration to increase and its credit terms to deteriorate. This is a tall order in light of the documented positive association between customer concentration and firm profitability — a relation that we verify in our data. To alleviate concerns about estimation biases, we experiment with a testing approach that uses M&A waves in customers' industries (downstream industry mergers) as an instrument for concentration. Downstream M&A activity is a plausible instrument for two reasons. First, it is related to customers' own growth prospects (see Erel, Jang, and Weisbach, 2015; Fee and Thomas, 2004) and following mergers in customer industries, suppliers face higher customer concentration (*inclusion restriction*). Second, downstream M&A activity is not a policy variable for suppliers and need not affect their borrowing terms through channels other than customer–supplier linkages (*exclusion restriction*).[2] We go a step further and incorporate in our test strategy downstream M&A activity that is triggered by Acts and Orders by the Federal Government that alter prices, entry, and other elements of the competitive environment.[3] Our IV estimations confirm the prior that following high levels of M&A activity in downstream industries, firms observe higher customer-base concentration. This (instrumented) shift, in turn, leads to costlier, stricter borrowing terms, as well as shorter banking relationships, confirming our baseline tests.

Aside from increasing loan markups, customer concentration is also related to higher profitability (Patatoukas, 2012). More profitable firms tend to receive lower loan rates as higher cash flows may absorb losses and prevent default. As such, our reduced-form estimates are limited in that they only show the effect of customer concentration on loan contract terms net of the effect from profitability. Indeed, the estimation of models with interactive effects suggests that at a very high level of profitability, the detrimental impact of customer concentration on bank credit is reduced. In other words, profitability modulates the impact of customer concentration on loan spreads. To gauge the direct impact of customer concentration, we estimate systems of equations that take into account the joint dynamics of loan markups, profitability, and customer concentration. We do so using both a three-stage-least-square (3SLS) and a generalized method of moments (GMM) approach. Estimations from both approaches suggest that, despite its positive impact on profitability, customer-base concentration is associated with higher loan markups.

Our empirical investigation further characterizes the channels through which customer concentration affects the credit terms offered by banks. As highly regulated intermediaries, banks are acutely concerned about loan underperformance. If higher customer concentration is associated with higher rates of loan underperformance, banks should naturally impose stricter loan terms. To examine this conjecture, we identify loan failures by matching our sample with the corporate default database used in Chava and Jarrow (2004) and Chava, Stefanescu, and Turnbull (2011). We find a positive, significant relation between customer concentration and loan failure rates. To wit, a one-standard-deviation increase in a firm's customer

[2] Bearing in mind concerns that suppliers' industry-level, time-varying dynamics could influence customers' M&A activity and credit terms, we further account for industry-year-fixed effects in our tests. To avoid contagion effects, we also remove data from firms whose secondary SIC codes coincide with their customers' SIC codes. A number of proxies capturing industry competitive dynamics are further added to the analyses.

[3] Examples of Federally mandated Acts and Orders that we use include the Natural Gas Wellhead Decontrol Act of 1989, the Energy Policy Act of 1992, the Trucking Industry and Regulatory Reform Act of 1992, and the Telecommunications Act of 1996.

concentration leads to a 3-percentage-point increase in the likelihood that the firm files for bankruptcy before paying its bank loan. We note that the evidence regarding loan failures is important in substantiating our base results on loan pricing and non-pricing contract features. It demonstrates that customer concentration is a relevant risk factor for banks' lending decisions.

We dig deeper into the meaning of our results by examining whether and how the characteristics of a firm's large customers affect its credit terms. To do this, we consider various financial and operational dimensions: customers' financial condition, their use of trade credit, and their requirement for specific inputs in supply-chain relations. Customers in worse financial shape may face difficulties in maintaining purchase agreements and paying on time, eventually burdening their suppliers. Similarly, customers that pay for their purchases on delayed schedules may also raise concerns for the creditors of supplier firms. Likewise, customers who use specific inputs are likely to request relationship-specific investments from their suppliers, increasing the extent of the "hold-up" problem in the supply chain. Confirming the logic of these arguments, we find that loan spreads increase even more when a firm's large customers are likely to be distressed, carry large balances of accounts payable, and purchase more specific inputs.

As the last step of our investigation, we consider how product market competition shapes our findings. Recent studies show how competition prompts firms to resort to more conservative policies and banks to impose higher loan rates (see Fresard, 2010; Fresard and Valta, 2015; Valta, 2012). To the extent that product market competition may influence customer-base consolidation and loan markups, it is important that we consider the competitive environment faced both by supplier and customer firms. Accounting for a host of competition measures, including the threat of foreign entry (Fresard, 2010) and industry concentration (Hoberg and Phillips, 2010a, 2015), we still find a strong relation between customer concentration and loan contract terms. Our results show that although the competitive environment has an important impact on the dynamics of interest, it does not subside the relation between customer concentration and loan markups.

Our paper is related to several strands of literature. First, it speaks to a growing literature on the relation between customer concentration and profitability. Patatoukas (2012) argues that having fewer, larger customers helps firms achieve economies of scale by lowering overhead costs. Irvine, Park, and Yildizhan (2014) further show that the beneficial effects of customer concentration vary with suppliers' age. Like prior papers, we show that customer concentration is indeed associated with higher profitability. Using *creditors' perspective*, however, we show that customer concentration ultimately bears negative effects on firm creditworthiness, leading banks to impose costlier, stricter loan terms.

Our study is also related to existing work on how supply-chain relations and product market competition affect financial policies. Titman and Wessels (1988) and Allen and Phillips (2000) show that firms tend to procure unique assets when they rely on major customers. These firms have lower leverage because customer liquidation imposes high redeployment costs for their relationship-specific assets (see also Banerjee, Dasgupta, and Kim, 2008; Kale and Shahrur, 2007). Relatedly, firms' investment and financial policies are shown to be influenced by the competition they face in the product market (Fresard and Valta, 2015; Haushalter, Klasa, and Maxwell, 2007). We push this research forward by showing how several different features of debt contracting — e.g., interest rates, maturity, and covenants — relate to a firm's customer base, the nature of its investment, credit relations with its customers.

Finally, our study is related to the recent literature on the determinants of bank loan terms (examples are Cen, Dasgupta, Elkamhi, and Pungaliya, 2015; Graham, Li, and Qiu, 2008; Hertzel and Officer, 2012; Roberts and Sufi, 2009; Valta, 2012). Closer to our study, Valta shows that firms in competitive industries face higher loan spreads because competition increases cash flow risk. Hertzel and Officer report that firms face higher spreads following industry-rivals' bankruptcies, especially in competitive industries. Cen et al. find that supply-chain relations reduce informational asymmetries between firms and creditors in the long run. None of these papers considers the effect of customer concentration on loan terms.

The paper proceeds as follows. Section 2 develops testable hypotheses. Section 3 describes our data and methodology. Section 4 reports univariate analyses. Section 5 contains our baseline regression results. Section 6 reports our instrumental variable analyses. Section 7 accounts for the interplay between customer concentration, profitability, and loan contract terms. Section 8 reports tests of the effect of customer concentration on loan failure rates. Section 9 shows how various characteristics of a firm's major customers affect the firm's borrowing terms. Section 10 accounts for various effects of product market competition. Section 11 concludes.

2. Hypotheses development

Having a concentrated customer base can bear complex implications for a firm's creditors. Prior studies document that firms with high levels of customer concentration are more profitable (Patatoukas, 2012). In addition, having major customers may signal to banks that a firm is of better quality (Cen, Dasgupta, Elkamhi, and Pungaliya, 2015). At the same time, major customers present a significant risk factor for a firm's cash flows and liquidity management. Major customer–supplier ties often involve the supplier committing into relationship-specific investments [see Banerjee, Dasgupta, and Kim, 2008; Kale and Shahrur, 2007; Titman and Wessels, 1988, for empirical evidence]. These investments cater to the needs of major customers, and may involve expenditures with R&D, unique assets, and customization of standard manufacturing processes [see Bolton and Scharfstein, 1998 for a theoretical framework]. Although major customers may offer more generous terms in return, firms conducting these investments face a higher uncertainty of success and limited resale options of the output to alternative users. Accordingly, although potentially lucrative, relationship-specific investments are risky for the firm (Rauch, 1999; Shleifer and Vishny, 1992; Titman, 1984).

The existing literature also argues that large customers often attain higher bargaining power over purchase prices and the timing of payments. Bhattacharyya and Nain (2011) and Fee and Thomas (2004) document that as customers become larger through mergers, they exert price pressure on their suppliers. Murfin and Njoroge (2014) further show that large customers often delay payments, elongate receivable cycles for upstream firms, who in turn, are forced to cut investments due to liquidity constraints.

Suppliers that are dependent on a select group of customers also face the risk of losing sales when those customers suffer from financial distress, or decide to change their product or vendor structure. Cohen and Frazzini (2008) and Kolay, Lemmon, and Tashjian (2016) show that a firm's investors recognize the negative news to its major customers and adjust their valuation downward. Hertzel and Officer (2012) show that bankruptcy filings and financial distress lead to measurable wealth losses to the shareholders of supplier firms. Itzkowitz (2013) documents how firms become concerned about losing important customers, holding more cash as precaution.

Taken together, the existing literature shows that concentration in the customer base can lead to more specific investments, liquidity problems, and increased cash flow risks, all of which can induce a higher likelihood that a firm defaults on its debt obligations. Anticipating higher loan default rates associated with customer concentration, banks should require higher returns on their loans. We write this central prediction as follows:

Hypothesis 1. Banks should impose costlier, stricter loan contract terms on firms with higher customer-base concentration.

Taking into account the characteristics of large customers, we derive a number of auxiliary hypotheses. First, as its customer base becomes more concentrated, a firm is more affected by the possibility that one or more of its customers delay payment or file for bankruptcy. The firm's ability to pay back its loan will be thus closely tied to the financial conditions of the customer. Accordingly, banks should be concerned with worsening financial conditions of the firm's major customers, and further impose costlier, stricter loan contract terms. This hypothesis can be stated as follows:

Hypothesis 2. Banks should impose costlier, stricter loan contract terms on firms that face customers in worse financial condition.

Similarly, banks should also be concerned if a firm's major customer is able to postpone payments for its purchases from the firm. This may cause the firm to face liquidity shortages, stop the firm from making profitable investments, and even force it into distress (see Murfin and Njoroge, 2014). Accordingly, we hypothesize:

Hypothesis 3. Banks should impose costlier, stricter loan contract terms on firms that face customers with high balances of accounts payable.

Further, as claimants to borrowers' liquidation value in bankruptcy, banks should be concerned about the resale value of firms' assets. As deep supply-chain relations often involve relationship-specific investments, firms with a concentrated customer base tend to procure specific assets that have lower liquidation values (Allen and Phillips, 2000; Titman and Wessels, 1988). Customers in industries that require more specific assets as inputs are more likely to request their suppliers to conduct relationship-specific investments. With customers in these industries, a firm should receive bank loans with even higher markups and stricter contract terms as customer concentration increases. This hypothesis can be stated as follows:

Hypothesis 4. Banks should impose costlier, stricter loan contract terms on firms that face customers in industries that require specific assets as inputs.

Notably, the intuition regarding "costlier, stricter terms" can be applied to various features of standard loan contracts, including interest rate spread, maturity, and the presence of restrictive covenants. Our tests will revolve around each of these observable outcomes: loan markups, loan maturity, loan covenants, and loan failures. We expand on this set of relationship variables and also examine how customer concentration affects derivative measures of the economic links between supplier firms and their banks: depth and duration of lending relationships.

Finally, one can further hypothesize about the reason banks impose costlier loan terms on firms with concentrated customer bases. As highly regulated institutions, banks are concerned about the risk of default by borrowers. As customer concentration may lead firms to undertake riskier investments and face liquidity shortage, we should see them defaulting more on their loans. We propose the following testable hypothesis:

Hypothesis 5. Firms with higher customer-base concentration should experience higher loan failure rates.

We set out to test these hypotheses in the remainder of our analysis.

3. Sample construction and empirical methodology

We identify firms' major customers using Compustat's Segment Customer database. Statement of Financial Accounting Standard (SFAS) No. 14 requires firms to report all customers that represent 10% or more of a firm's total sales. The Segment database collects information including the names of the customers and their assigned sales figures. In identifying customer relations, we focus on recurring customers and exclude those that appear for fewer than three times for a firm in the sample period. We focus on manufacturers (SIC 2000–3999) to ease the data collection process, to facilitate comparisons across firms (reduce unobserved heterogeneity), and because firms operating in this sector relate more naturally to our supply-chain focus. Indeed, information from the U.S. input–output matrix suggests that supplier–customer links in the manufacturing sector feature firms on both ends of the relationship.[4]

We extract bank loan contract information from LPC–Dealscan and link loan-level data to Compustat firm data following Chava and Jarrow (2004). We treat each loan facility as an independent contract. We examine revolvers and term loans since these types of loans contain more detailed information on the pricing and the restrictiveness of bank credit.

We construct our final sample by combining the customer and bank loan databases from 1985 through 2010. For a firm to be included in the sample, we require it to have available customer information, basic loan features, and information on standard variables such as size, leverage, and market-to-book. We glean into how banks update loan pricing and other contracting features by focusing on newly initiated (or renegotiated) loans during the year when the firms report customer information. Following the existing literature (e.g., Campello, Lin, Ma, and Zou, 2011; Hertzel and Officer, 2012; Lin, Ma, Malatesta, and Xuan, 2011; Valta, 2012), we do not repeatedly account for the same loans for the years after initiation. Our sample consists of 3,375 loans granted to 1,110 individual manufacturers.

3.1. Customer concentration

The literature does not provide a consistent way of measuring customer concentration. Previous studies use a variety of measures, most of which are computations based on the percentage of firm sales to major customers (examples are Banerjee, Dasgupta, and Kim, 2008 and Patatoukas, 2012). These approaches fit conveniently our framework of analyzing customer concentration. We experiment with several measures of concentration meant to capture the importance of a firm's large customers.

Our first measure of concentration is based on the percentage of sales that a firm assigns to its major customers (similar to Banerjee, Dasgupta, and Kim, 2008). In particular, we define *CustomerSales* as the sum of the percentage sales coming from the set of customers the firm reports as "major customers" (i.e., those with at least 10% of total sales). *CustomerSales* is computed as:

$$CustomerSales_i = \sum_{j=1}^{n_i} \%Sales_{ij},$$

where n_i is the number of firm i's major customers, and $\%Sales_{ij} = \frac{Sales\ of\ i\ to\ j}{Total\ Sales\ of\ i}$, is the percentage sales from firm i to customer j over i's total sales. A high level of *CustomerSales* means that a large proportion of a firm's sales goes to its major customers.

Our second measure is the sales-weighted size of a firm's major customers. This measure is more nuanced than the first in that it gives more importance to major customers that also happen to be larger firms; likely more significant supply-chain partners. We define *CustomerSize* as the firm's percentage sales to major customers weighted by the size of those customers. *CustomerSize* is computed as follows:

$$CustomerSize_i = \sum_{j=1}^{n_i} \%Sales_{ij} \times Size_j,$$

where $Size_j$ is the size (defined by log of total assets) of customer j. A high level of *CustomerSize* means that a firm relies more heavily on fewer, larger-sized customers.

Our third measure follows Patatoukas (2012), who defines concentration based on the notion of a Herfindahl index of sales to large customers:

$$CustomerHHI_i = \sum_{j=1}^{n_i} \%Sales_{ij}^2.$$

Expanding on this later approach, we also compute the Gini coefficient of a firm's sales to its large customers, a measure we call *CustomerGini*. Conversely, a simpler approach is based on the percentage sales a firm assigns to its single largest customer, $CustomerMax = \max_{j=1,\ldots,n_i} \%Sales_{ij}$. Alternatively, the simple count of the number of large customers provides an indication of the extent to which a firm deals with few, major customers, $CustomerCount = n_i$.

These six different measures provide unique insights about the extent to which a firm is engaged in trades with major customers in its supply-chain. While we conduct the bulk of our analysis based on the first two measures, we often report results for other measures as well (see Appendix B).

3.2. Borrowing terms

Chava and Roberts (2008), Chava, Stefanescu, and Turnbull (2011), and Campello, Lin, Ma, and Zou (2011) describe the elements of the LPC–Dealscan dataset that are relevant for our analysis. We follow the methodology in Campello et al. and measure three contract features of bank loan terms. The first is loan spread (*LoanSpread*). *LoanSpread* is the "All-in-drawn" spread (in basis-points) over LIBOR. "All-in-drawn" spread is computed as the sum of coupon and annual fees on the loan in excess of six-month LIBOR. The second feature is loan maturity (*LoanMaturity*). *LoanMaturity* is the number of months until maturity. Finally, we count the total number of restrictive covenants present in the loan facility (*LoanCovenants*).

3.3. Banking relationships

In addition to adjusting the terms of new loan facilities, banks can also react to a firm's customer concentration by abbreviating their relationships with the firm. If customer concentration is related to excessive credit risk or undesirable investment choices, banks can reduce the amount of funds lent to firms or even terminate their relations. We design empirical measures of firm–bank relationships to capture these dynamics.

Each time a firm discloses its customer concentration, we look forward in the sample window searching for subsequent loan arrangements (renewed relations in the future) with its current banks. We measure these future relations using two methods. First, we measure the additional

[4] Over two-thirds of output in those industries is sold as intermediary goods to other manufacturers, the remainder largely goes to bulk retailers.

amount of lending extended by the bank to the firm given the information of customer concentration (*FutureLoans*). *FutureLoans* is defined as the total dollar amount of loans issued by the same bank following the currently observed agreement, scaled by the dollar amount of current loans. Higher values of *FutureLoans* suggest that the bank maintains a stronger relationship with the firm after the disclosure of information about customer concentration.

Our second measure of firm–bank relations is the length of the future credit relationships, defined as the number of months in which the bank continues to lend to the firm in the future (*FutureDuration*). For each year a firm receives a bank loan, *FutureDuration* counts the number of months until the last occurrence of the firm receiving a loan from the current bank. Similar to *FutureLoans, FutureDuration* also reflects a bank's commitment to the lending relationship. However, it emphasizes the length rather than the intensity of the relationship.

Naturally, both measures of banking relationships suffer from attrition bias, as we observe shorter future duration and less future lending as we approach the end of the sample. We thus restrict our banking relationship tests to fiscal years prior to 2007.[5]

3.4. Loan failures

To corroborate our argument that a more concentrated customer base is associated with worse creditworthiness, we also examine the relation between loan failure rates and customer concentration. If customer concentration is associated with a higher likelihood of loan failure, banks will naturally impose stricter loan terms ex ante.

We examine this conjecture using bankruptcy data from Sudheer Chava's collection of corporate bankruptcies.[6] This database provides a comprehensive coverage of bankruptcy filings over the 1962–2010 window. We match the bankruptcy data with bank loan information and identify a loan failure event if the borrower files for bankruptcy prior to an existing loan maturity date. For this case, we assign an indicator variable *LoanFailure* equal to one. If there is no bankruptcy before the maturity of the loan, then *LoanFailure* is set to zero. We match the loan failure variable with firms' customer information and identify 210 loan failures in our sample.

3.5. Empirical methodology

We estimate panel regression models for our baseline tests that build on a large literature on bank loans (see, among others, Campello, Lin, Ma, and Zou, 2011; Graham, Li, and Qiu, 2008 and Campello, Lin, Ma, and Zou, 2011). Our basic models regress loan term variables on customer concentration measures together with standard firm-level, loan-level, and macro-level controls. The specifications also feature bank effects, capturing firm-bank pairings. The model can be written as follows:

$$\begin{aligned} LoanTerm_{i,k,t} &= \beta_0 + \beta_1 CustomerConcentration_{i,t} \\ &+ \beta_2 FirmCharacteristics_{i,t} \\ &+ \beta_3 MacroVariables_t + \beta_4 LoanCharacteristics_{k,t} \\ &+ \sum_g Industry_g + \sum_h Bank_h + \epsilon_{i,k,t}, \end{aligned} \tag{1}$$

where i indicates the supplier, k indicates newly initiated loans, t indicates the year of the loan initiation; *LoanTerm*$\in$ {*LoanSpread, LoanCovenants, LoanMaturity*}, and *CustomerConcentration* $\in$ {*CustomerSales, CustomerSize*}. Borrowing terms and customer concentration may vary significantly across industries. We thus include industry-fixed effects ($Industry_g$). Differences of borrowing terms can also arise from banks' screening technology. Some banks may be able to better detect firms' credit quality or to more closely monitor the firms. These banks may select firms with lower customer concentration and impose looser borrowing terms. We thus include bank-fixed effects ($Bank_h$). Note that the unit of observation is a loan contract. As such, we only observe within-firm variation if the firm signs contracts in different years. This results in few recurrences for each firm. Given the data structure, similar to prior studies in the loan literature, we are unable to include firm-fixed effects in our regressions. We report heteroskedasticity-robust errors clustered by firm and year.

Firm characteristics include size, age, profitability, tangibility, market-to-book, leverage, and credit ratings. Macroeconomic conditions are measured by the credit spread, the term spread, and the GDP growth rate. Loan characteristics include loan maturity, loan size, and loan spread. We also include a dummy variable for loan type (term loans or revolvers). A detailed definition of the variables is provided in Appendix A.

We conjecture that customer concentration has negative implications for firm borrowing terms. Therefore, we expect the coefficient on customer concentration, β_1, to be positive in the regressions for loan spreads and for the number of covenants. In the regression for loan maturity, we expect that coefficient to be negative.

We estimate analogous models for the link between customer concentration and future firm-bank relationships as follows:

$$\begin{aligned} BankingRelationship_{i,h,t} &= \beta_0 + \beta_1 CustomerConcentration_{i,t} \\ &+ \beta_2 FirmCharacteristics_{i,t} + \beta_3 MacroVariables_t \\ &+ \sum_g Industry_g + \sum_h Bank_h + \epsilon_{i,h,t}, \end{aligned} \tag{2}$$

where h indicates the lending bank and *Banking Relationship* $\in$ {*FutureLoans, FutureDuration*}. We expect customer concentration to hamper firms' future relationships with their banks. Therefore, we expect the coefficient β_1 to be negative in both banking relationship regressions.

3.6. Summary statistics

Table 1 reports the summary statistics of the suppliers' characteristics, customer concentration, loan terms, and banking relationship measures in our sample. The firms sampled attribute about 30% of their sales to major customers. These firms, on average, have total assets of

[5] Nonetheless, our results are unaffected if we do not impose this time window constraint.

[6] We thank Sudheer Chava for kindly providing these updated data.

Table 1
Summary statistics.
This table shows the summary statistics of the firm characteristics variables, customer variables, and loan term variables. The sample spans the 1985–2010 window, featuring manufacturing firms (SIC 2000–3999) in Compustat that have available firm characteristics and loan term variables. All continuous variables except leverage and the number of covenants (count) are winsorized within 5th and 95th percentiles. Leverage is restricted to the 0–1 range. See Appendix A for variable definitions.

Variables	Mean	Std. Dev.	p25	p50	p75	#Obs
LoanSpread	179.16	109.33	75	175	275	3,375
LoanMaturity	46	22	29	48	60	3,384
LoanCovenants	1.80	1.65	0	2	3	3,454
FutureLoans	4.43	5.41	1.08	2.39	5.67	1,410
FutureDuration	57.22	46.29	24	44	74	1,410
CustomerSales	0.30	0.20	0.15	0.23	0.39	3,454
CustomerSize	2.72	1.86	1.29	2.05	3.48	3,358
CustomerLeverage	0.09	0.08	0.03	0.06	0.11	3,358
CustomerDefault	0.30	0.26	0.12	0.20	0.38	3,358
CustomerPayable (*Payable/Sales*)	0.03	0.03	0.02	0.03	0.05	3,319
CustomerPayable (*Payable/COGS*)	0.03	0.02	0.01	0.02	0.04	3,319
CustomerSpecificity (*Differentiated input*)	0.28	0.22	0.11	0.19	0.42	1,560
CustomerSpecificity (*Non-homogeneous input*)	0.33	0.22	0.14	0.25	0.46	1,560
Size	6.38	1.62	5.13	6.41	7.61	3,454
Age	18.41	16.45	5	12	31	3,454
Profitability	0.12	0.11	0.08	0.13	0.18	3,436
Tangibility	0.26	0.15	0.15	0.24	0.37	3,451
M/B	1.71	1.06	1.12	1.38	1.91	3,454
Leverage	0.33	0.21	0.18	0.31	0.45	3,454
Ratings	0.48	0.50	0	0	1	3,454
LoanType	0.28	0.45	0	0	1	3,454

$590 million, asset tangibility of 26%, and leverage of 33%. These figures are similar to those in Campello, Lin, Ma, and Zou (2011), among others, who report total asset of $680 million, tangibility of 33%, and leverage of 29%. The average loan contracts in our sample have spreads of 179 basis points over LIBOR, maturity of 46 months, and 1.8 covenants.

4. Univariate analysis

We start our investigation by characterizing the very phenomenon of customer concentration, which is still understudied. Prior research points to significant gains in concentrating sales to a small group of buyers. These benefits arise from the argument that firms can achieve economies of scale and superior operating efficiency (Irvine, Park, and Yildizhan, 2014; Patatoukas, 2012). It is important that we verify these benefits in our data. Otherwise, one could attribute the worsening of borrowing terms that we document to potentially negative effects of customer concentration on operating performance. Along similar lines, we conjecture that customer concentration may be associated with other firm characteristics that influence their credit terms. Although our multivariate analyses are designed to address concerns about confounding heterogeneity effects, it is important that we have a basic understanding of these relations. As we show next, customer concentration is related to firm fundamentals such as size, age, and technology.

4.1. Customer concentration and firm operating performance

We depict the relation between customer concentration and operating performance in Fig. 1. Following Patatoukas (2012), we rank firms into deciles according to their customer concentration measure *CustomerSales* and plot the average operating performance of firms in each decile. The left (right) panel shows the average sales growth (profitability) of firms in each customer concentration level. Sales performance and profitability both increase with customer concentration. Firms in the lowest deciles of customer concentration, for example, observe average annual sales growth of about 9%, while those in the highest deciles observe 13% or higher growth (nearly 50% higher growth rates). The patterns we document in Fig. 1 are consistent with Patatoukas's argument that firms with concentrated customer bases enjoy improved performance (see also Irvine, Park, and Yildizhan, 2014). Important for our purposes, those patterns show that firms with high customer concentration are not "worse firms" who observe lower profits and should naturally face costlier, stricter loan terms.

4.2. Customer concentration and firm characteristics

Customer concentration can be correlated with important firm characteristics such as size, age, leverage, and market-to-book. We explore the relation of customer concentration with these firm characteristics, since they may also affect credit terms.

Fig. 2 shows that customer concentration is negatively related to firm size and age, indicating that smaller, younger firms tend to deal more frequently with major customers.[7] This association can lead to spurious correlation between customer concentration and loan terms, since smaller, younger firms also tend to face more

[7] To depict the process of customer-base concentration across firms' "life cycle," we only include in the figure firms whose life spans exceed ten years. Yet, including firms who exist in the sample for fewer than ten years does not change our inferences.

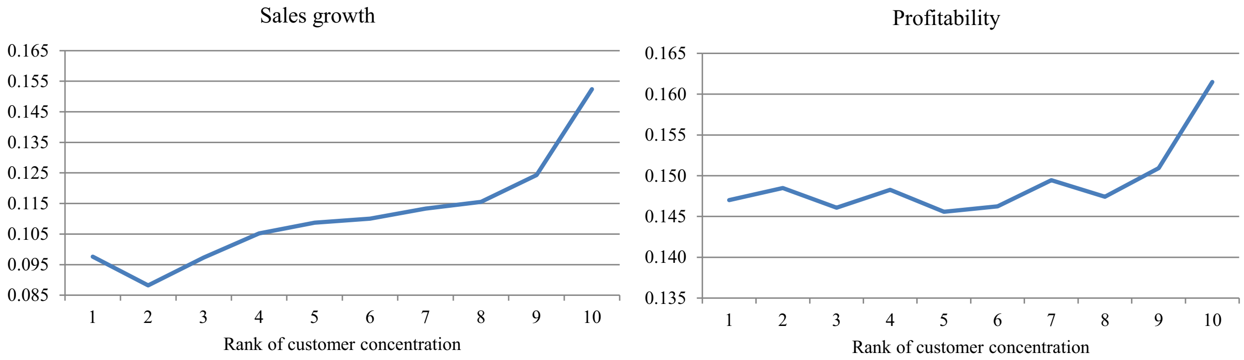

Fig. 1. The relation between customer concentration and firm operating performance. The left panel shows the relation between customer concentration and profitability; the right panel shows the relation between concentration and sales growth. Customer concentration is measured by the total percentage sales to all major customers, *CustomerSales*. The decile ranking of *CustomerSales* is shown on the horizontal axes. The sample spans the 1985–2010 window, including Compustat firms that have available firm characteristics and customer information. See Appendix A for variable definitions.

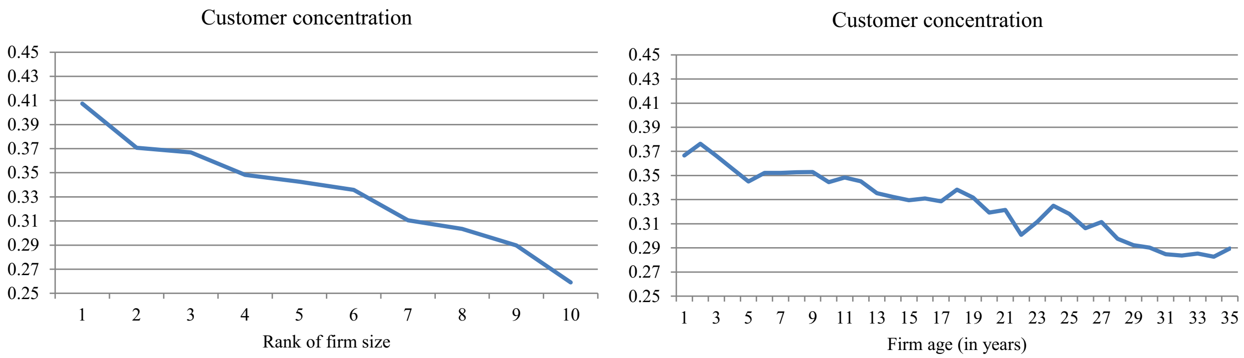

Fig. 2. The relation between customer concentration with firm size and age. The left panel shows the relation of size with customer concentration, where the horizontal axis shows the decile ranking of firm size. The right panel shows the relation of firm age with customer concentration, where the horizontal axis shows firm age. Customer concentration is measured by the total percentage sales to all major customers, *CustomerSales*. The sample spans the 1985–2010 window, including Compustat firms that have available firm characteristics and customer information. See Appendix A for variable definitions.

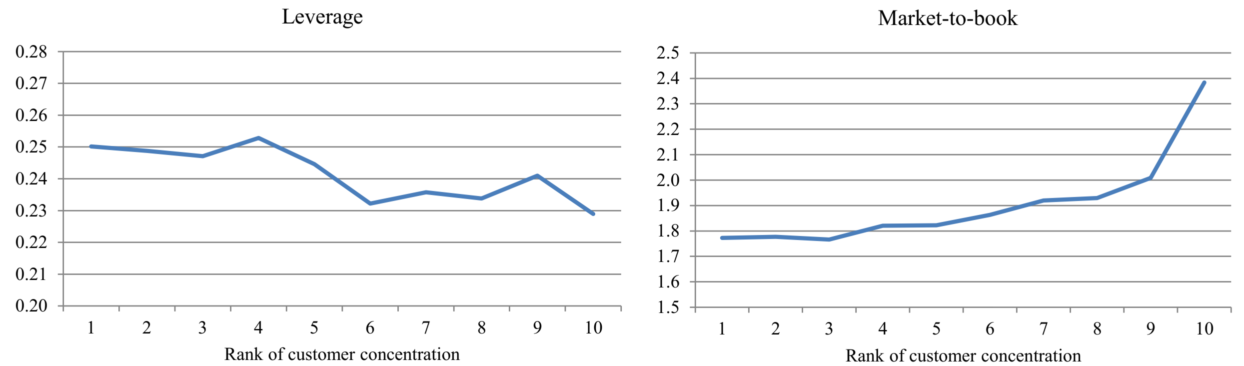

Fig. 3. The relation between customer concentration with firm leverage and market-to-book. The left panel shows the relation between customer concentration and firm leverage. The right panel shows the relation between concentration and market-to-book. Customer concentration is measured by the total percentage sales to all major customers, *CustomerSales*. The decile ranking of *CustomerSales* is shown on the horizontal axes. The sample spans the 1985–2010 window, including Compustat firms that have available firm characteristics and customer information. See Appendix A for variable definitions.

informational problems, hence higher borrowing costs. It is thus important to control for firm size and age effects in our tests.

Fig. 3 provides further insights into firms that operate with higher levels of customer concentration. Concentration is associated with lower leverage ratios. It is also associated with higher market-to-book ratios. Notably, research shows that firms with lower leverage and higher market-to-book are able to command lower interest rate spreads in their bank loans (e.g., Graham, Li, and Qiu, 2008). These findings corroborate the argument that firms with major customers are not underperforming businesses that are naturally prone to receive costlier, stricter loan terms from their banks.

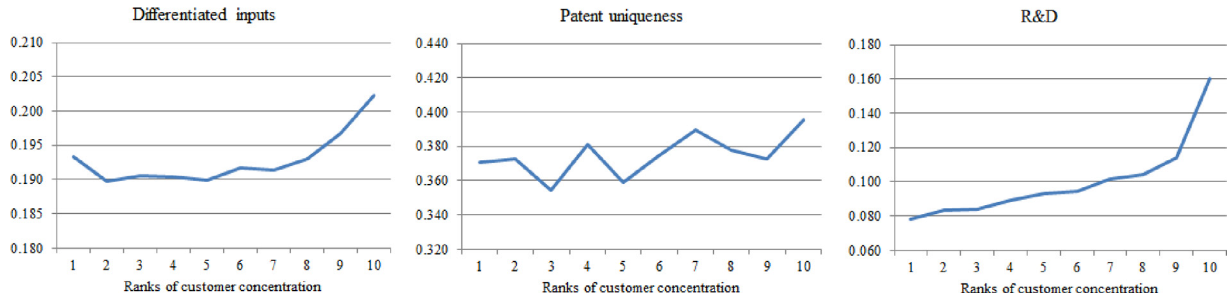

Fig. 4. The relation between customer concentration and relationship-specific investments. The left panel shows the relation of customer concentration with firms' uniqueness of inputs, measured by the percentage of firms' inputs from industries producing differentiated goods; the middle panel shows the relation of concentration with the originality of patents; and the right panel shows the relation of concentration with R&D intensity. Customer concentration is measured by the total percentage sales to all major customers, *CustomerSales*. The decile ranking of *CustomerSales* is shown on the horizontal axes. The sample spans the 1985–2010 window, including Compustat firms that have available firm characteristics, customer information, and measures of relationship-specific investments.

4.3. Customer concentration and relationship-specific investment

Prior research shows that important customers often require a higher level of relationship-specific investment (Bolton and Scharfstein, 1998; Titman and Wessels, 1988). As a firm's customer base becomes more concentrated, it is natural to conjecture that an important customer can more easily contract with the firm to invest in customized projects that are suitable to its particular needs. Firms that do not have to cater to a major customer, on the other hand, only need to manufacture standardized products. We study this argument by examining the relation between customer concentration and relationship-specific investment. While it is difficult to measure relationship-specific investment, we gauge the uniqueness of firms' investment following the existing literature.

Our first measure focuses on the level of differentiated inputs firms use. In particular, we examine how specific are the inputs they employ in their production process. Firms that use more differentiated inputs have been shown to offer more differentiated products to their customers, and we use this metric to gauge the depth of their relationship. Rauch (1999) and Giannetti, Burkart, and Ellingsen (2011) provide detailed information on industries' use of differentiated inputs. We follow Giannetti, Burkart, and Ellingsen (2011)'s approach and assign a firm to a given level of differentiated inputs usage according to the industry in which it operates. Our second measure is based on the uniqueness of firms' patents. We gather information on firms' patents from the NBER database and focus on "patent uniqueness," measured by the width of different patents cited in the creation of firms' granted patents (see Hall, Jaffe, and Trajtenberg, 2001 for details). Firms with more unique patents are thought to develop and sell more unique, customized products to their customers. Finally, we measure relationship-specific investments using firms' R&D intensity, defined as the ratio of firms' R&D expenditure scaled by total assets (Allen and Phillips, 2000; Kale and Shahrur, 2007).

Fig. 4 points to a positive relation between firms' relationship-specific investments and customer concentration. The plots in the figure suggest that firms that have higher customer concentration use more specific inputs for production, produce more original patents, and invest more in R&D. These patterns are consistent with the economics of our testable hypotheses. They are also consistent with theories of optimal stakeholder investment and the limits of the firm, which predict that a firm's relations with its important stakeholders will involve relationship-specific investments (e.g., Hart, 1995; Titman, 1984).

5. Baseline regression analysis

We estimate panel regression models of loan spreads, the number of restrictive covenants, loan maturity, and future banking relationship variables (length and depth) on each of our measures of customer concentration. In each estimation run, we first control for firm-level characteristics, industry-fixed effects, and bank-fixed effects. We then augment the model with macro variables as controls. In the last round, we further include loan-level characteristics as controls. Tables 2–5 present results for 22 such models.

Table 2 shows the results for regressions of loan spreads on measures of customer concentration, *CustomerSales* and *CustomerSize*. Both measures attract significant and positive coefficients across all estimations, suggesting that firms with a higher customer concentration are asked to pay higher spreads in their bank loan facilities. The most conservative set of estimates in the table (column 6, featuring the full set of controls) suggests that a one-standard-deviation increase in customer concentration is associated with an 11 basis point increase in the loan spread. This amounts to a 6% increase relative to the average loan spread of 179 basis points. The results suggest that banks consider customer concentration as a negative factor affecting firms' credit quality; a factor that is priced into loan markups.

Table 3 shows results for the number of restrictive covenants. Both measures of customer concentration attract positive and statistically significant coefficients across all regressions, suggesting that firms with high customer concentration have more restrictive covenants written in their new loan contracts. The estimates from column 6 indicate that a one-standard-deviation increase in customer concentration is associated with a 0.2 increase in the

Table 2
Loan spreads and customer concentration.
This table shows the relation between loan spreads and customer concentration. The dependent variable is All-in-drawn loan spread (*LoanSpread*). All regressions use industry-fixed effects and bank-fixed effects. Industry is classified as two-digit SIC industry and the lending banks are classified by their ultimate parents. Robust-clustered *t*-statistics are shown in parentheses. Columns 1 through 3 show the regression results for *CustomerSales*: the sum of the percentage sales to the set of customers a firm reports as "major customers." Columns 4 through 6 show the regression results for *CustomerSize*: the total size of all major customers, weighted by the firm's percentage sales to these customers. See Table 1 for sample descriptions and Appendix A for variable definitions.

Dep. var.:	*CustomerConcentration* is *CustomerSales*			*CustomerConcentration* is *CustomerSize*		
LoanSpread	(1)	(2)	(3)	(4)	(5)	(6)
CustomerConcentration	52.56***	47.14**	46.39**	7.05***	5.90***	5.67***
	(2.93)	(2.42)	(2.46)	(3.63)	(2.77)	(2.74)
Size	−27.58***	−28.28***	−18.08***	−28.11***	−28.64***	−18.17***
	(−7.16)	(−9.13)	(−5.77)	(−7.23)	(−9.22)	(−5.81)
Age	−0.78***	−0.96***	−0.77***	−0.80***	−0.98***	−0.79***
	(−3.55)	(−4.38)	(−3.79)	(−3.70)	(−4.58)	(−3.96)
Profitability	−272.89***	−260.23***	−257.22***	−292.40***	−284.38***	−279.04***
	(−4.98)	(−4.92)	(−5.04)	(−5.59)	(−5.66)	(−5.74)
Tangibility	−20.65	−4.89	−6.54	−16.13	−1.90	−2.23
	(−0.81)	(−0.22)	(−0.35)	(−0.63)	(−0.09)	(−0.12)
M/B	−11.07***	−6.58*	−4.96	−9.23**	−4.60	−3.16
	(−2.59)	(−1.88)	(−1.56)	(−2.33)	(−1.48)	(−1.08)
Leverage	135.13***	146.97***	123.87***	138.60***	149.30***	125.21***
	(6.48)	(8.35)	(7.10)	(6.70)	(8.65)	(7.36)
Ratings	38.08***	37.98***	41.51***	37.94***	38.06***	41.59***
	(3.98)	(4.38)	(4.83)	(3.80)	(4.25)	(4.74)
CreditSpread		87.21***	87.43***		82.11***	82.81***
		(2.69)	(2.77)		(2.61)	(2.71)
TermSpread		1.74	2.44		2.98	3.62
		(0.30)	(0.44)		(0.53)	(0.68)
GDPGrowth		−3.96	−4.12		−4.18	−4.38
		(−0.84)	(−0.85)		(−0.87)	(−0.89)
LoanMaturity			0.18			0.21
			(1.20)			(1.39)
LoanSize			−15.97***			−16.46***
			(−5.51)			(−5.31)
LoanType			48.51***			47.59***
			(9.58)			(8.91)
Observations	3,045	3,045	2,983	2,965	2,965	2,903
R-squared	0.45	0.52	0.57	0.45	0.52	0.58

*** p-value$<$ 0.01,
** p-value$<$ 0.05,
* p-value$<$ 0.10.

number of restrictive covenants, which accounts for a 12% increase relative to the average number of covenants (1.8 covenants) for the loans in the sample.

Table 4 shows results for loan maturity. In this set of regressions, only term loans are considered since revolvers do not set fixed loan maturities. Both measures of customer concentration attract negative coefficients, suggesting that firms with higher customer concentration receive loans with shorter maturity. The statistical significance of these estimates is less strong. In economic terms, however, a one-standard-deviation increase in customer concentration is associated with a two-month reduction in loan maturity; compared to the average maturity of 46 months.

We also study the impact of customer concentration on length and depth of the relationship of the supplier firm and its bank. The results are reported in Table 5. The most conservative estimates in the table suggest that a one-standard-deviation increase in customer concentration is associated with a decline in the amount of future lending extended by the firm's bank equivalent to 10% of the sample mean. A one-standard-deviation increase in concentration is associated with eight fewer months of future relations with the bank; a 17% drop from the mean.

The results in Tables 2–5 are internally coherent and consistent with our proposed set of hypotheses. They show that a more concentrated customer base is associated with costlier, stricter loan terms for the firm's loans, including higher interest rate spreads, more restrictive covenants, and shorter maturities. Customer concentration is also associated with the deterioration of firm-bank associations, captured by shorter relations and less lending by the bank in the future.

6. An instrumental variables approach

Although common in the loan contracting literature, regressions such as those performed in the previous section are subject to several concerns about estimation biases. Concerns about endogeneity, in particular, may arise from the fact that the model lacks an explicit source of exogenous variation in concentration. To allay those concerns, this section conducts instrumental variables (IV) tests that

Table 3
Number of restrictive covenants and customer concentration.
This table shows the relation between the number of restrictive covenants written on bank loans and customer concentration. The dependent variable is the number of loan covenants (*LoanCovenants*). All regressions use industry-fixed effects and bank-fixed effects. Industry is classified as two-digit SIC industry and the lending banks are classified by their ultimate parents. Robust-clustered *t*-statistics are shown in parentheses. Columns 1 through 3 show the regression results for *CustomerSales*. Columns 4 through 6 show the regression results for *CustomerSize*. See Table 1 for sample descriptions and Appendix A for variable definitions.

Dep. var.:	*CustomerConcentration* is *CustomerSales*			*CustomerConcentration* is *CustomerSize*		
LoanCovenants	(1)	(2)	(3)	(4)	(5)	(6)
CustomerConcentration	1.04**	1.01**	0.83**	0.12***	0.11***	0.09**
	(2.54)	(2.45)	(2.37)	(2.73)	(2.62)	(2.48)
Size	−0.24***	−0.23***	−0.22***	−0.24***	−0.24***	−0.21***
	(−3.14)	(−3.50)	(−3.40)	(−3.16)	(−3.49)	(−3.34)
Age	−0.01	−0.01	0.01	−0.01	−0.01	0.01
	(−0.78)	(−0.92)	(0.65)	(−0.87)	(−0.98)	(0.58)
Profitability	0.79	0.83	1.38***	0.66	0.73	1.28**
	(1.42)	(1.49)	(2.62)	(1.24)	(1.32)	(2.41)
Tangibility	−0.53	−0.39	−0.21	−0.58	−0.46	−0.29
	(−1.16)	(−0.85)	(−0.45)	(−1.25)	(−0.99)	(−0.61)
M/B	−0.15*	−0.13*	−0.08	−0.13*	−0.12	−0.07
	(−1.91)	(−1.79)	(−1.18)	(−1.65)	(−1.59)	(−1.05)
Leverage	0.73**	0.72**	−0.08	0.74**	0.73**	−0.07
	(2.26)	(2.28)	(−0.20)	(2.28)	(2.28)	(−0.18)
Ratings	0.20	0.19	0.05	0.20	0.19	0.06
	(1.25)	(1.28)	(0.41)	(1.21)	(1.27)	(0.45)
CreditSpread		1.46*	1.19		1.38*	1.15
		(1.95)	(1.55)		(1.91)	(1.51)
TermSpread		−0.11	−0.11		−0.10	−0.10
		(−0.96)	(−1.02)		(−0.92)	(−0.98)
GDPGrowth		0.21*	0.25*		0.21*	0.24*
		(1.65)	(1.79)		(1.68)	(1.78)
LoanSpread			0.01***			0.01***
			(5.98)			(5.92)
LoanMaturity			0.01**			0.01***
			(2.41)			(2.67)
LoanSize			0.11**			0.09**
			(2.35)			(2.04)
LoanType			0.08			0.06
			(1.24)			(0.86)
Observations	3,055	3,055	2,983	2,975	2,975	2,903
R-squared	0.17	0.19	0.26	0.17	0.19	0.26

*** p-value $<$ 0.01,
** p-value $<$ 0.05,
* p-value $<$ 0.10.

exploit sharp shifts in the concentration of a firm's customer base.

We use merger and acquisition activity in *customers'* industries (downstream M&A) as an instrument in assessing the impact of customer concentration on *suppliers'* loan terms and banking relationships. Our instrumental approach implies that suppliers will face a more concentrated customer base following M&A waves in their customers' industries (*inclusion restriction*). Existing research supports such a prior (e.g., Bhattacharyya and Nain, 2011; Fee and Thomas, 2004) and we verify that this is indeed the case in the tests below. The approach also assumes that downstream M&A may only affect suppliers' borrowing terms through customer–supplier links (*exclusion restriction*). This is a plausible assumption since downstream M&A activity (among customers) is not a policy variable for the supplier. Yet, that activity may be influenced by suppliers' industry dynamics that could ultimately affect both suppliers' customer bases and their financial conditions, thus the terms of their loans. To control for these dynamics, as we discuss below, we further introduce suppliers' industry-level, time-varying effects in our tests. In a later section (Section 10), we go further and explicitly consider the influence of dynamics engendered, for example, by industry concentration or import penetration.

6.1. Measuring M&A activity in the customer industry

We gather information on M&A deals from SDC database and apply a series of data filters following Ahern and Harford (2014): 1) only include completed deals; 2) both the acquirer and target are U.S. firms; 3) the acquirer can be matched with a Compustat identifier; 4) the acquirer purchases at least 20% of the target during the transaction, and owns at least 51% after the transaction; and 5) the acquirer does not buy its suppliers. We exclude suppliers who are in the same two-digit SIC industry as their customers.

We use the transaction values of M&As scaled by the acquirers' total sales as a proxy for acquisition activity. An industry-level five-year mean acquisition activity is measured as the average acquisition of firms in the industry

Table 4
Loan maturity and customer concentration.
This table shows the relation between the bank loan maturity (in months) and customer concentration. The dependent variable is loan maturity (*LoanMaturity*). Only term loans are considered for this test. All regressions use industry-fixed effects and bank-fixed effects. Industry is classified as two-digit SIC industry and the lending banks are classified by their ultimate parents. Robust-clustered *t*-statistics are shown in parentheses. Columns 1 through 3 show the regression results for *CustomerSales*. Columns 4 through 6 show the regression results for *CustomerSize*. See Table 1 for sample descriptions and Appendix A for variable definitions.

Dep. var.:	*CustomerConcentration* is *CustomerSales*			*CustomerConcentration* is *CustomerSize*		
LoanMaturity	(1)	(2)	(3)	(4)	(5)	(6)
CustomerConcentration	−15.37*	−14.15*	−8.00*	−1.77*	−1.65*	−1.00**
	(−1.71)	(−1.71)	(−1.81)	(−1.73)	(−1.75)	(−1.99)
Size	5.04	3.55	−2.88**	3.74	1.81	−2.96**
	(1.27)	(0.96)	(−2.18)	(0.98)	(0.51)	(−2.20)
Age	−1.55***	−1.10*	−0.20**	−1.43**	−0.83	−0.18**
	(−2.69)	(−1.66)	(−2.56)	(−2.50)	(−1.24)	(−2.35)
Profitability	41.81	34.80	44.40***	45.16	40.35	44.51***
	(1.08)	(1.05)	(4.11)	(1.14)	(1.20)	(4.03)
Tangibility	−32.62	−30.82	−19.29***	−35.37	−29.92	−19.70***
	(−1.05)	(−1.07)	(−3.03)	(−1.16)	(−1.06)	(−2.92)
M/B	−0.27	−0.46	−3.34**	−3.15	−4.29	−3.59***
	(−0.07)	(−0.11)	(−2.50)	(−0.74)	(−1.21)	(−2.69)
Leverage	8.18	6.95	6.13	8.80	7.70	6.03
	(0.71)	(0.63)	(1.14)	(0.79)	(0.71)	(1.10)
Ratings	8.45	7.11	3.90	9.15	7.63	3.25
	(1.20)	(1.06)	(1.25)	(1.32)	(1.13)	(1.04)
CreditSpread		14.54*	−3.68		12.72	−3.04
		(1.70)	(−0.64)		(1.50)	(−0.51)
TermSpread		−1.93	−0.84		−1.87	−1.03
		(−1.42)	(−0.96)		(−1.36)	(−1.17)
GDPGrowth		3.26*	2.35**		3.45*	2.45**
		(1.80)	(2.32)		(1.84)	(2.34)
LoanSpread			0.01			0.01
			(0.46)			(0.85)
LoanSize			4.21***			4.46***
			(3.54)			(3.69)
Observations	903	903	894	879	879	870
R-squared	0.23	0.27	0.29	0.23	0.27	0.30

*** p-value $<$ 0.01,
** p-value $<$ 0.05,
* p-value $<$ 0.10.

over the past five years. Each of the firms in our sample supplies products to a portfolio of customers, and those customers may be in different industries. As such, for each sample firm, we gauge the impact of downstream M&A activity on customer concentration by taking the weighted sum of the five-year acquisition activity across the industries to which the firm's customers belong, weighted by the firm's percentage sales to each customer. We refer to this variable as *CustomerM&A*. The variable is defined as follows:

$$CustomerM\&A_i = \sum_{j=1}^{n_i} \%Sales_{i,j} \times Industry\ Average\left(\frac{Acquisition_j}{Sales_j}\right).$$

6.2. Supplier–customer relationship changes following downstream mergers

To corroborate the inclusion restriction of our IV strategy, we examine the changes in the sales of a firm to its major customer after that customer has conducted a horizontal acquisition. As the customer consolidates with another firm in its industry, we expect it to establish a stronger buyer position (see Fee and Thomas, 2004; Bhattacharyya and Nain, 2011). Fig. 5 shows the normalized sales amount from a firm to an acquirer in a merger deal around the year the merger becomes effective. To document the growth in customer sales, we normalize the supplier's sales around the merger; scaling it by the amount of sales to the acquirer in the year prior to the merger. Fig. 5 suggests that sales to acquirer customers are stable before downstream mergers. Following those mergers, however, sales increase quickly, with 30% growth in the same year of merger and 80% growth after two years since completion. Sales are twice as large as the pre-merger level in just five years.[8]

The pronounced growth in sales that we document implies that suppliers of an acquirer observe an increasing concentration of its customer base. On the flip side, the same process highlights the increased risk of losing this important customer. Table 6 documents examples of mergers in various industries where acquirers go through

[8] This phenomenon will be captured by the first-stage regression of our IV model.

Table 5
Future bank relationships and customer concentration.
This table shows the relation between future bank relationships to a firm and the firm's customer concentration. The dependent variable is future bank relationships, as measured by the total amount of lending extended by the same bank scaled by the current amount of lending (*FutureLoans*) and the duration of banking relationships in the future (*FutureDuration*). All regressions use industry-fixed effects and bank-fixed effects. Industry is classified as two-digit SIC industry and lending banks are classified by their ultimate parents. Robust-clustered *t*-statistics are shown in parentheses. Columns 1 and 2 show the regression results for *CustomerSales*. Columns 3 and 4 show the regression results for *CustomerSize*. See Table 1 for sample descriptions and Appendix A for variable definitions.

	CustomerConcentration is *CustomerSales*		*CustomerConcentration* is *CustomerSize*	
Dep. var.:	(1) *FutureLoans*	(2) *FutureDuration*	(3) *FutureLoans*	(4) *FutureDuration*
CustomerConcentration	−1.73*	−38.70***	−0.23*	−4.97***
	(−1.66)	(−3.24)	(−1.75)	(−3.60)
Size	0.12	−1.28	0.06	−1.40
	(0.59)	(−0.55)	(0.25)	(−0.60)
M/B	−0.02	−0.31**	−0.01	−0.31**
	(−1.04)	(−2.38)	(−0.77)	(−2.32)
Profitability	6.91***	65.50***	7.01***	63.78***
	(3.46)	(3.90)	(3.60)	(3.65)
Tangibility	2.99**	29.55**	3.44**	31.84***
	(2.30)	(2.44)	(2.41)	(2.63)
M/B	0.73**	3.05	0.78**	2.82
	(2.23)	(1.44)	(2.13)	(1.39)
Tangibility	−1.16	−2.93	−1.40	−4.91
	(−1.16)	(−0.25)	(−1.34)	(−0.42)
Ratings	0.42	13.75***	0.43	13.92***
	(0.74)	(2.72)	(0.69)	(2.73)
CreditSpread	−0.48	−21.04	−0.19	−18.82
	(−0.31)	(−0.90)	(−0.12)	(−0.81)
TermSpread	0.42	2.83	0.39	2.83
	(1.03)	(0.50)	(0.95)	(0.51)
GDPGrowth	−0.18	−0.46	−0.20	−0.46
	(−0.88)	(−0.13)	(−0.85)	(−0.13)
Observations	1,271	1,271	1,239	1,239
R-squared	0.16	0.20	0.15	0.19

*** p-value $<$ 0.01,
** p-value $<$ 0.05,
* p-value $<$ 0.10.

significant changes in their supplier bases. For example, Cardinal Health acquired several firms in the pharmaceutical industry in 2006. Around these mergers, it ended relationships with 12 existing suppliers, including Accentia Biopharmaceuticals and Genentech. Concurrently, six other suppliers reported to start new supply-chain relationships with Cardinal Health. As shown in Table 6, mergers in other industries, such as the acquisitions made by GE in 1998, IBM in 2002, as well as Motorola in 1998 and 1999, are also associated with high occurrences of supply-chain relationship changes.

To show formally that mergers engender changes in supply-chain relationships, we estimate the likelihood of losing a major customer following downstream industry mergers within our sample of manufacturing firms. Documenting this underlying tension substantiates concerns that mergers (and customer consolidation) pose a threat to customer–supplier relations, thus customer–bank relations.[9] For each customer–supplier pair in our sample, we measure the intensity of merger activity (defined as the industry deal values scaled by acquirers' sales) that occurs in the customer's industry during the span of the customer–supplier relationship. We then partition the sample into terciles of this merger intensity measure and calculate the number of years following the merger event that customer–supplier relationship lasted. Fig. 6 describes the probability that a relationship will end in the years after mergers occur in downstream industries. The striped columns show the likelihood of a relationship ending for low levels (bottom tercile) of merger activity in the customer's industry. The solid columns show the likelihood for high levels (top tercile) of merger activity. In both terciles, customer relationships are likely to end in the first ten years following the merger event. Notably, however, a customer–supplier relationship will more likely end within the first two years following a high level rather than a low level of merger activity in the customer's industry. The turnover of supply-chain relationships following downstream mergers points to a higher risk of losing major customers due to mergers.

6.3. IV specification

We use two-stage-least-square regressions to assess the impact of customer concentration on loan terms. In the first stage, we regress customer concentration measures (*CustomerSales* and *CustomerSize*) on *CustomerM&A*, together with a full set of controls. In the second stage, we

[9] We thank our referee for suggesting this examination.

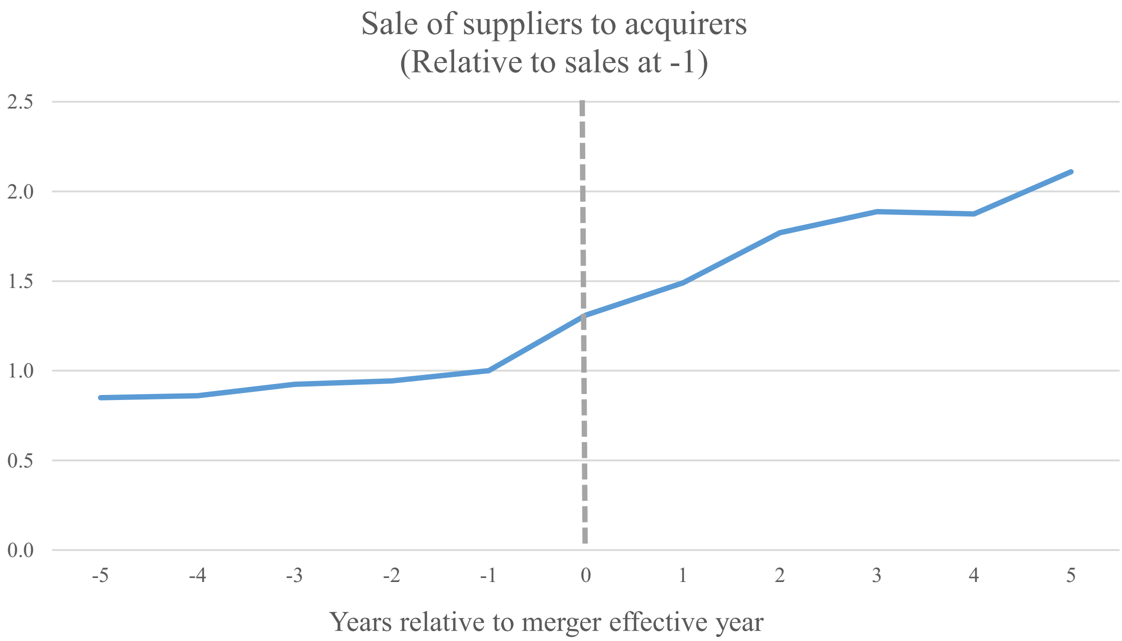

Fig. 5. Sales to acquirers. This figure shows the average sales of an upstream firm to an acquirer around the year that its merger becomes effective. Sales are normalized by the amount in the year prior to the merger effective date. The horizontal axis shows the number of years past the merger effective year, and the vertical axis shows the normalized sales amount. The sample includes all Compustat manufacturing (SIC 2000–3999) firms whose downstream firms experience at least a merger. We also require these firms to have available firm characteristics and customer information.

Table 6
Examples of relationship changes following mergers.

This table shows examples of how customer–supplier relationships change around merger events. The first column shows the names of acquirers, the second column shows the year that mergers became effective, and the third column presents the names of the firms acquired. The fourth column displays the names of suppliers with whom the acquirers began new relationships after their mergers. Finally, the last column displays the names of suppliers with whom the acquirers ended relationships after their mergers.

Acquirer	Merger year	Target	Begin new relationship with	End relationship with
Cardinal Health	2006	ParMed Pharma, F Dohmen Co-Pharm Whl, MedMined, Denver Biomedical	Amylin Pharma, Cornerstone Therapeutics, Impax Lab, Savient Pharma, Valeant Pharma, Warner Chilcott	Accentia Biopharma, Barr Pharma, Bradley Pharma, Celgene, Collagenex Pharma, Cytogen, Genentech, Medicines, Medimmune, Nabi Biopharma, Sciele Pharma, Sepracor
GE	1998	Power Factor Correction, Lockheed Martin-Bus Units, Raytheon Systems Ltd Flight	Cardiodynamics, Catalytica Energy, Colorado Medtech, Fairfield Manufacturing, Global Power Equipment	Clark (Dick) Productions, Doncasters, Fischer Imaging, Gilat Satellite Networks, Henley, Howmet intl, Intermagnetics General, Wyman-Gordon, Zing Technologies
IBM Corp	2002	Access360, PwCC, CrossWorlds, TrelliSoft, Holosofx	Halifax, Qlogic, Sanmina, Steel Excel, Teltronics, Volterra Semiconductor	Alternative Resources, BTU intl, En Pointe Technologies, FSI intl, Hutchinson Technology, IBIS Technology, Magnetek, Manufacturers Services, Midgardxxi, Neoware, Perficient
Motorola Inc	1998–1999	Ring Zero Software, Starfish Software, Lucent Technologies-Wireless &Bbroadcom, Software Corp of America, Pinnacle Towers Inc-Comm, Metrowerks Corp	Advanced Semicon Engineering, Anadigics, Catapult Comm, CTS, Frequency Electronics, Pemstar, Strasbaugh	Aseco, Atmel, Clare, Cohu, Collabrx, Essex, Green st. Energy, Parlex, Pixtech, Premisys Communications, Sheldahl, Silicon Valley Grp, Technisource, Xetel

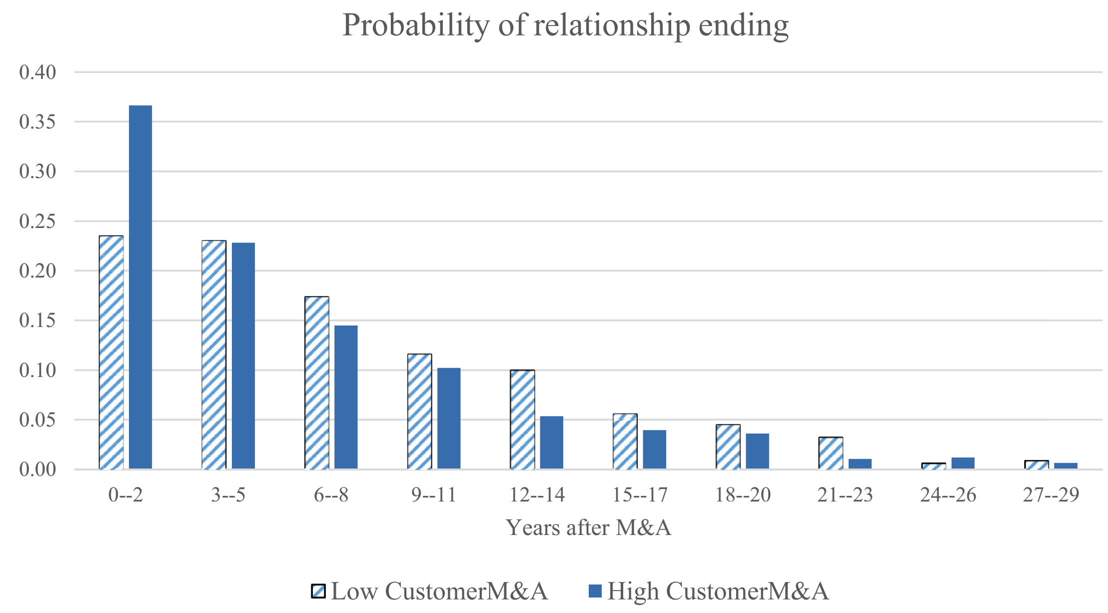

Fig. 6. Probability of losing customers following mergers. This figure depicts the likelihood of a customer relationship ending in years following M&A activity in that customer's industry. The striped columns show the likelihood of a relationship ending when the customer's industry experiences a low level of merger activity. The solid columns show the likelihood when the customer's industry experiences a high level of merger activity. The horizontal axis shows the number of years after mergers occur. See Fig. 5 for sample descriptions.

regress borrowing terms and banking relationship variables on the projected customer concentration measures, together with controls. The two-stage system for loan terms can be written as follows:

$$CustomerConcentration_{i,k,t} = \beta_0 + \beta_1 CustomerM\&A_{i,t} + Controls + \epsilon_{i,k,t} \quad (3a)$$

$$LoanTerms_{i,k,t} = \beta_2 + \beta_3 \widehat{CustomerConcentration}_{i,k,t} + Controls + \nu_{i,k,t}, \quad (3b)$$

where i indicates the supplier, k indicates loans, t indicates the fiscal year. *LoanTerms* includes the loan term variables *LoanSpread*, *LoanCovenants*, and *LoanMaturity*. *CustomerConcentration* indicates customer concentration measures. $\widehat{CustomerConcentration}$ denotes the predicted value of customer concentration from the first-stage regression (Eq. (3a)), reflecting the variation of customer concentration induced by the variation of M&A activity in customers' industries. *Controls* contains the set of control variables used in our baseline regressions, including firm-level controls, macro variables, loan-level controls, and various fixed effects.

Our IV tests further account for unobserved industry dynamics that can drive both downstream merger waves and firms' credit terms. These industry-wide shocks may further propagate along the supply chain and affect all firms in the system. To control for industry-level, time-varying dynamics that may confound our results, we further incorporate supplier industry-year-fixed effects in our specifications. The fixed effects approach removes any unobservable shock that is common to an industry in a given time period, preventing it from contaminating the exclusion restriction of our instrument.

The two-stage system for banking relationships can be written as:

$$CustomerConcentration_{i,h,t} = \beta_0 + \beta_1 CustomerM\&A_{i,t} + Controls + \epsilon_{i,h,t} \quad (4a)$$

$$BankingRelationship_{i,h,t} = \beta_2 + \beta_3 \widehat{CustomerConcentration}_{i,h,t} + Controls + \eta_{i,h,t}, \quad (4b)$$

where h indicates the lending bank. *BankingRelationship* is the measures for bank relationships: *FutureLoans* and *FutureDuration*.

In the first stage Eqs. (3a) and (4a)), we expect β_1 to be positive, indicating that suppliers experience increases in customer concentration following high levels of M&A activity in the customers' industries. In the second stage, we expect β_3 to be positive for the loan spreads and covenants regressions, and negative for the loan maturity and bank relationship regressions.

6.4. IV results

Table 7 shows the first-stage regression results for customer concentration on customer industry acquisition activity (*CustomerM&A*). The instrument loads significantly positively in all models. To cut clutter, we only present results for our first concentration measure, *CustomerSales*. Tabulations for *CustomerSize* are similar and readily available.

Results in Table 7 are consistent with the prior of our identification strategy implying that firms face more concentrated customer bases following M&A activity in their customers' industries (see Fig. 5). In economic terms, a

Table 7
First-stage results for IV estimations.
This table shows the first-stage regression results of a firm's customer concentration (*CustomerSales*) on the average customers' industry acquisition activity (*CustomerM&A*). All regressions use industry-year-fixed effects and bank-fixed effects. Robust-clustered *t*-statistics are shown in parentheses. See Table 1 for sample descriptions and Appendix A for variable definitions.

Dep. var. in the second stage:	(1) *LoanSpread*	(2) *LoanCovenants*	(3) *LoanMaturity*	(4) *FutureLoans*	(5) *FutureDuration*
CustomerM&A	7.29***	7.21***	7.05***	6.71***	6.89***
	(11.91)	(11.99)	(5.64)	(10.80)	(8.25)
Size	−0.01*	−0.01	0.01	−0.01**	−0.01**
	(−1.86)	(−1.23)	(0.04)	(−2.18)	(−2.24)
Age	−0.01	−0.01	−0.01	−0.01*	−0.01*
	(−1.55)	(−1.23)	(−0.65)	(−1.87)	(−1.78)
Profitability	0.12	0.15*	0.09	0.02	0.02
	(1.55)	(1.91)	(0.45)	(0.30)	(0.22)
Tangibility	−0.03	−0.03	−0.04	−0.01	−0.02
	(−0.64)	(−0.68)	(−0.44)	(−0.06)	(−0.29)
M/B	−0.01*	−0.01*	−0.01	−0.01	−0.01
	(−1.83)	(−1.69)	(−0.67)	(−1.27)	(−0.98)
Leverage	−0.01	−0.03	−0.03	−0.03	−0.03
	(−0.31)	(−0.84)	(−0.60)	(−1.03)	(−0.79)
Ratings	−0.01	−0.01	−0.03	0.02	0.01
	(−0.56)	(−0.88)	(−0.89)	(0.94)	(0.42)
LoanSpread		0.01*	0.01*		
		(1.79)	(1.87)		
LoanMaturity	0.01	0.01			
	(0.35)	(0.13)			
LoanSize	0.01	0.01	0.01		
	(1.18)	(1.60)	(0.37)		
LoanType	−0.01	−0.01			
	(−0.84)	(−1.48)			
Observations	1,957	1,957	570	857	857
First-stage *F*-test	141.78	143.81	31.78	115.61	68.10
p-value	<0.01	<0.01	<0.01	<0.01	<0.01
Kleibergen-Paap LM Stat	49.09	49.99	24.38	34.70	29.39
p-value	<0.01	<0.01	<0.01	<0.01	<0.01

*** p-value$<$ 0.01,
** p-value$<$ 0.05,
* p-value$<$ 0.10.

one-standard-deviation increase in downstream M&A contributes to an 11% increase in customer concentration, which is a 40% increase relative to the average customer concentration. Notably, the *F*-statistics from the first-stage regressions pass the weak identification tests at the 1% level. The Kleinberg-Paap statistics easily pass the associated under-identification tests.

Table 8 shows the second-stage regression results of loan terms and banking relationships on the instrumented customer concentration. Consistent with our OLS results, the instrumented customer concentration is positive and statistically significant in the loan spread and loan covenants regressions. Also consistent with the OLS results, the coefficients associated with customer concentration are negative and statistically significant in the loan maturity and future banking relationship regressions. To see that the economic interpretation of the IV results are comparable with our earlier findings, note that a one-standard-deviation of the predicted measure $\widehat{CustomerConcentration}$ is 0.16. According to estimations in Table 8, a one-standard-deviation change in this measure is associated with 12-basis-point higher loan spreads, 0.18 more loan covenants, and 4.5 months shorter loan maturity for the suppliers of the merging industries.

The IV estimations confirm our earlier findings that increases in customer concentration lead to higher loan spreads and more loan covenants for supplier firms. Higher customer concentration also leads to lower loan maturity, shorter banking relationships, and less lending extended by the same bank in the future. In all, the evidence we gather suggests that while customer concentration may make supply-chain relations more profitable (more on this shortly), a deeper exposure to a small set of customers also has negative consequences for a firm's relations with its creditors.

6.5. Strategy validation: regulatory-induced M&A activity

The merger activity we exploit in our IV tests is spontaneous and one could be concerned that unobserved developments or trends affecting the supplier firms we study could: 1) lead to changes in the contracting terms those firms receive from their banks, and simultaneously 2) trigger M&A activity among their customers in downstream industries. It is ultimately hard to completely rule in or rule out such a claim, but we take one extra step at ensuring that this is not a concern for the results obtained from our IV tests. We do so using a test strategy that relies solely on downstream M&A activity that is triggered by Federal Government Acts that change entry, prices, and other elements of the competitive environment of the downstream industry affected. Ample literature shows that

Table 8
Second-stage results for customer concentration.
This table shows the second-stage results of the relation between a firm's customer concentration and both its borrowing terms and future bank relationships. Customer concentration measures are instrumented with the acquisition levels in the customer's industries (*CustomerM&A*). The dependent variables include loan spreads (*LoanSpread*), number of loan covenants (*LoanCovenants*), loan maturity (*LoanMaturity*), and future bank relationships as measured by the future amount of loans extended by the same bank, scaled by the current loan amount (*FutureLoans*) and the duration of banking relationships in the future (*FutureDuration*). *CustomerConcentration* is the projected customer concentration from the first-stage regressions. Customer concentration is measured by *CustomerSales*. All regressions use industry-year-fixed effects and bank-fixed effects. Industry is classified as two-digit SIC industry and lending banks are classified by their ultimate parents. Robust-clustered *z*-statistics are shown in parentheses. See Table 1 for sample descriptions and Appendix A for variable definitions.

Dep. var.:	(1) *LoanSpread*	(2) *LoanCovenants*	(3) *LoanMaturity*	(4) *FutureLoans*	(5) *FutureDuration*
CustomerConcentration	74.66***	1.18**	−28.96**	−7.90**	−30.42**
	(2.88)	(2.01)	(−2.55)	(−1.97)	(−2.17)
Size	−22.97***	−0.20***	−1.60	0.58	4.49**
	(−7.17)	(−3.43)	(−1.10)	(1.29)	(2.55)
Age	−0.89***	−0.01	−0.25**	−0.01	−0.03
	(−5.39)	(−1.21)	(−2.36)	(−0.05)	(−0.29)
Profitability	−266.37***	1.42**	26.49*	14.42**	23.05
	(-6.19)	(2.17)	(1.89)	(2.21)	(1.11)
Tangibility	11.52	0.12	−0.35	0.30	−10.20
	(0.56)	(0.29)	(−0.04)	(0.09)	(−0.80)
M/B	−6.41*	−0.10*	−3.61**	1.06*	1.34
	(−1.93)	(−1.80)	(−2.15)	(1.88)	(0.85)
Leverage	129.81***	−0.38	−10.10	0.52	−3.87
	(8.29)	(−1.30)	(−1.57)	(0.21)	(−0.43)
Ratings	38.87***	0.02	12.09***	0.24	8.05*
	(4.65)	(0.13)	(3.41)	(0.22)	(1.91)
LoanSpread		0.01***	0.02		
		(4.36)	(1.20)		
LoanMaturity	0.29**	0.01***			
	(2.47)	(5.35)			
LoanSize	−14.22***	−0.02	3.12**		
	(−5.32)	(−0.39)	(2.22)		
LoanType	31.07***	0.01			
	(8.83)	(0.24)			
Observations	1,957	1,957	570	857	857
R-squared	0.77	0.59	0.68	0.27	0.66

*** p-value $<$ 0.01,
** p-value $<$ 0.05,
* p-value $<$ 0.10.

these actions have led to spikes in the M&A activity in the industries affected (e.g., Andrade, Mitchell, and Stafford, 2001; Bruner, 2004; Schoenberg and Reeves, 1999; and Ovtchinnikov, 2013). We use these induced spikes in M&A in a difference-in-differences framework.

There were eight major nation-wide regulatory actions applicable to our analysis in the sample period we examine: the Natural Gas Wellhead Decontrol Act (1989), the Cable Television Consumer Protection and Competition Act (1992), the Energy Policy Act (1992), the Federal Energy Regulatory Commission (FERC) Order 636 (1992), the Negotiated Rates Act (1992), the Trucking Industry and Regulatory Reform Act (1992), the Telecommunications Act (1996), and the FERC Order 888 (1996).[10] The affected ("deregulated") industries include natural gas, cable TV, trucking, telephone, and wholesale, defined at the four-digit SIC level.

We first verify claims by previous researchers that these Federally mandated Acts and Orders affecting the competitive environment had the end result of triggering M&A activity. We do so by comparing the M&A activity in the industries affected by regulation with the M&A activity in other (unaffected) industries that share the same three-digit SIC codes. As shown in Fig. 7, the average level of M&A activity (acquisition deal value scaled by total sales of acquirers) in the deregulated industries increased three-fold following a regulatory innovation. By comparison, the M&A activity in other industries sharing the same three-digit SIC code did not exhibit any change.

The next step of our analysis is to establish supplier–customer links for the industries affected by the eight regulatory events listed above. To identify the suppliers of these deregulated industries, we use the input–output (I–O) matrix provided by the Bureau of Economic Analysis. To closely capture input–output relations amongst industries in our sample period, we use the I–O matrix of 1987 for the regulatory event taking place in 1989, and the I–O matrix of 1992 for the events of 1992 and 1996. We first identify the suppliers of the deregulated industries, and examine the changes in firm-level customer concentration and loan contract terms for firms in the supplier industries.[11] In other words, we consider the suppliers of

[10] See (Asker and Ljungqvist, 2010) for a detailed summary of these deregulation events.

[11] We restrict suppliers to be in industries that attribute over 3% sales to the deregulated industries.

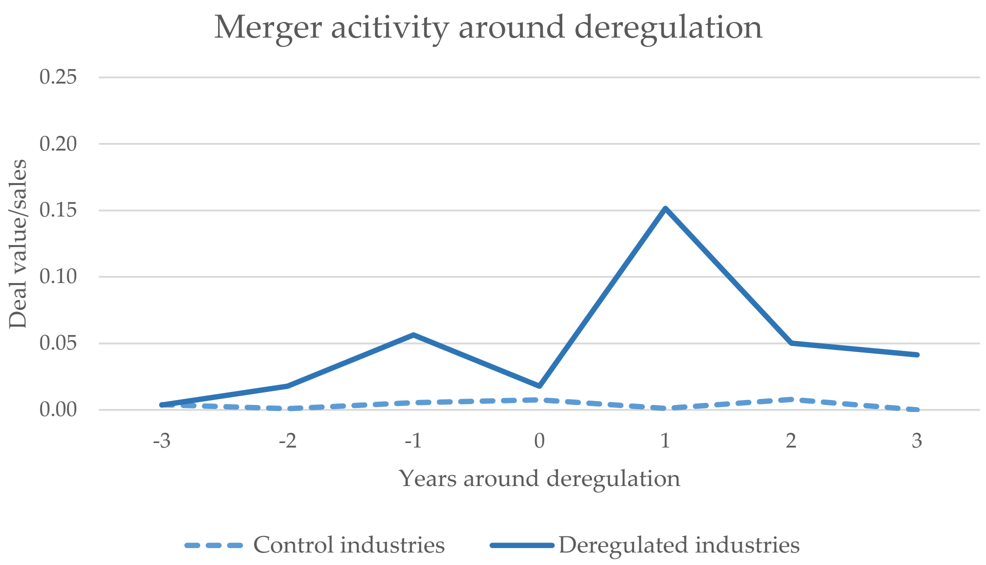

Fig. 7. M&A activity around deregulation. This figure shows the industry average level of M&A activity around deregulation events. The horizontal axis shows the number of years past the deregulation event, and the vertical axis shows the industry average level of M&A activity, measured by acquisition value scaled by sales. Deregulated industries are classified at the four-digit SIC level, while control industries include other firms in the same three-digit SIC industries as the deregulated firms, but with different four-digit SIC codes. The sample spans the 1986–2000 window, including all merger and acquisition deals from SDC database.

deregulated industries as our treated group. We define our control group as the other firms in the same three-digit SIC industries as these suppliers, but with different four-digit SIC codes (non-deregulated industries). In this way, we are able to keep similarity between treated and control groups both economically and in terms of sample size. We further restrict the event period to be from three years before to three years after each regulatory event

Using a difference-in-differences panel setup, we examine how regulatory-induced downstream mergers affect a firm's customer concentration and the loan contract terms it receives. Formally, we estimate the following regressions:

$$Y_{i,k,t} = \beta_0 + \beta_1 Treated_i + \beta_2 Post_t + \beta_3 Treated_i \times Post_t + Controls + \epsilon_{i,k,t}, \tag{5}$$

where i indicates the borrower, k indicates loans, t indicates the fiscal year. Outcome variable Y includes *CustomerSales* and *LoanSpread. Treated* is a dummy variable indicating whether a firm's customer industry experienced a Federally mandated Act or Order affecting its competitive environment. *Post* is a dummy variable covering the period following the regulatory event. Finally, *Controls* contains the set of control variables used in our baseline regressions, including firm-level controls, macro-level variables, loan-level controls, industry-fixed effects, and bank-fixed effects.

Table 9 reports the results from Eq. (5). Columns 1 and 2 show the results for customer concentration. The interaction term *Treated* × *Post* loads positively, indicating that the mergers driven by deregulation events increase the customer-base concentration for suppliers. Columns 3 and 4 show the results for loan markups, where the interaction term *Treated* × *Post* also loads positively. This result suggests that creditors become concerned about firms whose customers concentrate following regulatory acts, imposing higher interest rates on their loans.

The evidence we gather from tests around regulatory events are consistent with our prior results on the relation between customer concentration and credit terms. In particular, the study of downstream M&A activity triggered by Federal Acts and Orders supports the results of our larger IV-based tests; that is, firms' customer-base concentration can lead to costlier, stricter loan contract terms imposed by banks of their suppliers.

7. Profitability as a modulating factor

As we show in Section 4, having a concentrated customer base is often related to higher profitability. Profitable firms are charged lower loan rates because higher cash flows help mitigate credit risk. One limitation of our baseline estimates, however, is that they only show the "net effect" of customer concentration. To the extent that customer concentration increases profitability, one would like to assess whether profitability offsets the negative impact of customer concentration on markups.

To gauge the modulating effect of profitability on the relations that we document, we regress bank loan spreads on the interaction of customer concentration with indicators of firm profitability. The estimates show that for firms with a high level of profitability (top tercile of the profitability distribution), a one-standard-deviation increase in customer-base concentration is associated with an 8 basis point increase in loan spreads. For firms that have a low profitability level (bottom tercile), an equal increase in concentration is associated with 16 basis points higher spreads. Our OLS-based estimation thus suggests that profitability affects the degree to which customer concentration influences a firm's perceived credit risk. The result

Table 9
Customer concentration and loan spreads following deregulation events.

This table shows how customer concentration and loan spreads change following customer industries' deregulation events. The dependent variable in columns 1 and 2 is customer concentration, measured by *CustomerSales*. The dependent variable in columns 3 and 4 is loan spreads (*LoanSpread*). *Treated* is a dummy variable indicating whether a firm's customer industry experienced a Federally mandated Act or Order affecting its competitive environment. *Post* is a dummy variable covering the period following the regulatory event. All regressions use industry-fixed effects and bank-fixed effects. Industry is classified as three-digit SIC industry and lending banks are classified by their ultimate parents. Robust-clustered z-statistics are shown in parentheses. See Table 1 for sample descriptions and Appendix A for variable definitions.

Dep. var.:	*CustomerConcentration*		*LoanSpread*	
	(1)	(2)	(3)	(4)
Treated	0.01	0.01	−9.98	−7.10
	(0.54)	(0.48)	(−1.26)	(−1.15)
Post	−0.02***	−0.02***	5.08	6.68*
	(−3.12)	(−3.14)	(1.28)	(1.78)
Treated× *Post*	0.04***	0.04***	21.39**	12.55*
	(3.14)	(3.12)	(2.00)	(1.69)
Size	−0.05**	−0.07**	−6.48	−16.57
	(−2.65)	(−2.09)	(−0.33)	(−0.69)
Age	−0.01	0.01	−0.54	−0.99
	(−1.09)	(0.07)	(−0.60)	(−1.12)
Profitability	−0.08	−0.07	16.45	22.12
	(−0.65)	(−0.57)	(0.20)	(0.28)
Tangibility	0.22	0.16	−112.16	−136.75
	(1.41)	(0.95)	(−1.16)	(−1.16)
M/B	0.01	0.01	−17.01**	−9.57*
	(0.64)	(0.29)	(−2.51)	(−1.69)
Leverage	−0.07	−0.02	173.40***	136.35***
	(−1.07)	(−0.22)	(4.82)	(3.46)
Ratings	−0.03	−0.03	−31.72	−13.84
	(−0.57)	(−0.64)	(−1.54)	(−0.71)
CreditSpread	−0.31***	−0.29***	83.59	93.50
	(−4.00)	(−3.76)	(0.97)	(1.17)
TermSpread	−0.02	−0.03	−8.49	−7.08
	(−0.99)	(−1.31)	(−0.69)	(−0.59)
GDPGrowth	−0.01	−0.01	−2.66	−4.76
	(−1.22)	(−1.20)	(−0.45)	(−0.71)
LoanMaturity		−0.01**		−0.05
		(−2.53)		(−0.07)
LoanSize		0.03*		−0.55
		(1.77)		(−0.06)
LoanType		0.03*		55.59***
		(1.78)		(3.11)
Observations	216	211	212	207
R-squared	0.81	0.82	0.69	0.75

*** p-value< 0.01,
** p-value< 0.05,
* p-value< 0.10.

invites further investigation into the modulating effect of profitability on markups.

While informative, the OLS-based approach is less complete in dealing with the issue of simultaneity involving profitability and customer concentration. We next formally take into account the joint determination of customer concentration and profitability. First, we estimate a system of equations for *LoanSpread, Profitability*, and *CustomerConcentration* using three-stage-least-squares (3SLS). In this system of equations, we allow all three variables to affect one another. We regress each variable on the other two variables with the same set of controls as in Eq. (1), specifying a subset of the control variables as exogenously determined. The system of equations can be written as follows:

$$\begin{cases} LoanSpread_{i,k,t} = a_0 + a_1 CustomerConcentration_{i,t} \\ \quad + a_2 Profitability_{i,t} + a_3 Controls + \xi_{i,k,t} \\ Profitability_{i,k,t} = b_0 + b_1 CustomerConcentration_{i,t} \\ \quad + b_3 LoanSpread_{i,t} + b_3 Controls + \eta_{i,k,t} \\ CustomerConcentration_{i,k,t} = c_0 + c_1 LoanSpread_{i,t} \\ \quad + c_2 Profitability_{i,t} + c_3 Controls + \zeta_{i,k,t} \end{cases} \tag{6}$$

where *Controls* include firm characteristics, loan terms, macroeconomic conditions, and industry- and bank-fixed effects. Among the set of controls, we identify firm age, macroeconomic conditions, and industry and bank effects as exogenous. In this specification, we expect customer concentration to be associated with higher loan spreads and profitability with lower loan spreads. In short, we expect that $a_1 > 0$ and $a_2 < 0$.

Panel A of Table 10 shows the results from the 3SLS estimation. Column 1 shows the results for the *LoanSpread* equation. As expected, *CustomerConcentration* attracts a positive, significant coefficient in the *LoanSpread* model, while *Profitability* attracts a negative coefficient. The coefficient of *CustomerConcentration* indicates that a one-standard-deviation increase in concentration is associated with 32 basis points higher loan spreads. This estimate is higher than those from Table 2, suggesting that the OLS estimations bias downwardly the effect of customer concentration on markups; likely due to the offsetting effect from firm profitability. Column 2 shows the results for the *Profitability* equation, where *CustomerConcentration* attracts a positive, but small coefficient. Overall, results from the 3SLS estimation continue to show that customer-base concentration leads to costlier bank loans.

We further analyze the relations between loan spreads, profitability, and customer concentration using a generalized method of moments (GMM) approach. Similar to Eq. (6), we estimate a system of equations for *LoanSpread, Profitability*, and *CustomerConcentration*. In choosing the instruments for the moment conditions, we make the assumption that banks base their lending decisions according to a firm's current levels of customer concentration as well as profitability, placing less importance on past levels of this variable. The intuition is that the information contained in lagged variables is stale and already incorporated in current levels of these regressors. Under these assumptions, we choose as our instruments two lags of *CustomerConcentration* and *Profitability*. As a last set of added instruments, we consider an attribute of the firm's asset base, *Tangibility*, whose expansion path largely depends on the technological environment in which the firm operates. We include two lags of changes in *Tangibility* in the instrumental set.

Panel B of Table 10 shows the GMM results. Similar to the 3SLS results, *CustomerConcentration* is associated with significantly higher bank loan markups. At the same time, *Profitability* dampens this effect by reducing markups. The estimates point to a large, negative effect of customer-base concentration on markups as we separate out the direct effect of concentration from the indirect effect channeled through profitability. They suggest that, despite the higher cash flows brought about by customer-base concentration, concentration also engenders concerns about firms' ability

Table 10
The effect of profitability.
This table shows the relations between loan spreads, profitability, and customer concentration. Panel A reports results from a 3SLS approach, estimating a system of joint equations for loan spreads, profitability, and customer concentration. The exogenous variables are macroeconomic conditions, industry-fixed effects, bank-fixed effects, and firm age. Panel B shows results from a GMM estimation. The instruments are the first and second lags of *CustomerConcentration*, *Profitability*, and two lags of changes in *Tangibility*. *CustomerConcentration* is *CustomerSales*. Robust-clustered z-statistics are shown in parentheses. See Table 1 for sample descriptions and Appendix A for variable definitions.

Panel A: 3SLS			
	(1)	(2)	(3)
Dep. var.:	*LoanSpread*	*Profitability*	*CustomerConcentration*
CustomerConcentration	154.16***	0.02	
	(8.59)	(1.09)	
Profitability	−927.32***		0.08
	(−14.64)		(0.34)
LoanSpread		−0.01***	0.01***
		(−14.84)	(8.82)
Size	3.07	−0.01	−0.02
	(0.39)	(−0.21)	(−1.17)
Age	−0.29*	−0.01*	−0.01***
	(−1.71)	(−1.79)	(−3.45)
Tangibility	−35.93	0.02	0.37***
	(−1.33)	(1.00)	(5.20)
M/B	12.91**	0.01***	−0.05***
	(2.44)	(2.94)	(−3.73)
Leverage	231.18***	0.12***	−0.74***
	(8.00)	(4.60)	(−9.69)
Ratings	72.03***	0.06***	0.07
	(4.71)	(4.61)	(1.60)
LoanMaturity	1.36***	0.01**	−0.01***
	(3.27)	(2.56)	(−2.98)
LoanSize	−52.00***	−0.03***	0.08***
	(−4.91)	(−3.14)	(2.68)
LoanType	5.70	0.01	0.19***
	(0.22)	(0.63)	(2.83)
CreditSpread	81.97***	0.05***	−0.15***
	(7.61)	(4.66)	(−4.76)
TermSpread	5.12**	0.01***	−0.01
	(2.51)	(3.02)	(−0.74)
GDPGrowth	−4.56**	−0.01	0.01**
	(−2.40)	(−1.24)	(1.99)
Observations	2,983	2,983	2,983
R-squared	0.15	−0.03	−0.42

Panel B: GMM			
	(1)	(2)	(3)
Dep. var.:	*LoanSpread*	*Profitability*	*CustomerConcentration*
CustomerConcentration	153.30***	0.07***	
	(72.32)	(38.18)	
Profitability	−709.85***		13.22***
	(−385.99)		(178.4)
LoanSpread		−0.01***	0.02***
		(−238.79)	(210.39)

*** p-value $<$ 0.01,
** p-value $<$ 0.05,
* p-value $<$ 0.10.

to sustain their banking relationships. In particular, concentrating sales among a few major customers may ultimately lead suppliers to default on their loans. Relatedly, in the next section, we discuss how fears associated with credit exposure and contagion may explain banks' decision to offer worse loan terms when firms sell their output to larger customers.

8. Customer concentration and bank exposure

In this section, we substantiate the argument that firms with higher customer concentration face more adverse credit terms because of their deteriorated creditworthiness. Banks are highly regulated intermediaries and the exposure to loan risk bears tremendous costs for them. If customer concentration increases the likelihood of loan failure, it should be associated with costlier, stricter bank loan terms. In what follows, we match our customer and loan datasets with the Sudheer Chava's bankruptcy database (updated from Chava and Jarrow, 2004) to test the idea that customer concentration is related to loan failures. We end the section with a back-of-the-envelope calculation of the aggregate credit losses associated with customer concentration, showing how they evolve over time.

8.1. The likelihood of loan failures

To test the idea that a more concentrated customer base increases the likelihood a firm will default on its bank loans, we examine the relation between customer concentration and *LoanFailure*, an indicator for whether the firm files for bankruptcy before its outstanding loans mature. We estimate an IV model that is similar to that of Eq. (4), featuring *LoanFailure* as the dependent variable in the second-stage regression. The model is designed to gauge the dynamics through which downstream mergers alter a firm's customer-base concentration over the effective span of a bank loan contract (first stage); showing how increased customer concentration ultimately changes a supplier's loan default likelihood (second stage). To capture this dynamic, we consider the average level of downstream merger activity and customer concentration during the pre-default period of a loan. Given that bankruptcy in our sample occurs, on average, around 36 months after loan initiation dates, we measure *CustomerM&A* and *CustomerConcentration* using their average levels over the three years following the initiation of a loan contract.

Table 11 reports our IV-based results for models featuring *CustomerSales* and *CustomerSize* as customer concentration proxies. Results from the first stage show that our instrument, *CustomerM&A*, is positively related to *CustomerConcentration*, confirming the logic that downstream merger activity leads to a more concentrated customer-base for the supplier firm. In the second stage, both customer concentration variables have positive and significant coefficients, suggesting that firms with more concentrated customer bases are more likely to fail during the existence of a loan contract, thus exposing their banks to higher loan default risk. To help interpret our estimates, note that the coefficient for *CustomerSales* in column 2 suggests that a one-standard-deviation increase in customer concentration is associated with a 3.9-percentage-point increase in loan failure rates. This effect is sizable, given the average loan failure rate of 5.4%.[12]

[12] In unreported tables, we further verify that firms are more likely to fail on their loans as their customers' financial condition deteriorates (proxied by *CustomerLeverage* and *CustomerDefault*).

Table 11
Loan failure rate and customer concentration.
This table shows the relation between bank loan failure rates and customer concentration using an instrumental variable approach. The dependent variable is loan failure (*LoanFailure*), a dummy variable that equals one if a firm files for bankruptcy before loan maturity, zero otherwise. The instrument is *CustomerM&A*, the three-year average level of downstream merger activity following the loan initiation date. Columns 1 and 2 show the regression results for *CustomerSales*. Columns 3 and 4 show the regression results for *CustomerSize*. All regressions use industry-year-fixed effects and bank-fixed effects. Industry is classified as two-digit SIC industry and the banks are classified by their ultimate parents. Robust-clustered *z*-statistics are shown in parentheses. See Table 1 for sample descriptions and Appendix A for variable definitions.

Dep. var.: *LoanFailure*	*CustomerConcentration* is *CustomerSales*		*CustomerConcentration* is *CustomerSize*	
	(1)	(2)	(3)	(4)
Second-stage results				
CustomerConcentration	0.24**	0.25**	0.03**	0.03**
	(2.07)	(2.12)	(2.05)	(2.10)
Firm characteristics	Yes	Yes	Yes	Yes
Loan characteristics	No	Yes	No	Yes
Industry-year FEs	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes
Observations	2,134	2,086	2,123	2,075
R-squared	0.37	0.39	0.37	0.40
First-stage results				
CustomerM&A	34.40***	34.49***	310.01***	310.24***
	(13.17)	(12.75)	(12.71)	(12.34)
Firm characteristics	Yes	Yes	Yes	Yes
Loan characteristics	No	Yes	No	Yes
Industry-year FEs	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes
First-stage *F*-test	173.41	162.59	161.43	152.28
p-value	<0.01	<0.01	<0.01	<0.01
Kleibergen-Paap LM Stat	73.43	71.53	76.67	68.82
p-value	<0.01	<0.01	<0.01	<0.01

* *p*-value< 0.10,
*** *p*-value< 0.01,
** *p*-value< 0.05.

Our tests substantiate the idea that banks are concerned about suppliers' ability to honor their debt obligations in the face of high levels of customer-base concentration.

8.2. The impact of customer concentration on aggregate loan losses

It is important that we investigate if the default hazard that is caused by customer concentration generates significant magnitudes of monetary losses. To provide a rough estimate of such losses, we take the product of four pieces of information: 1) the face value of the average loan, 2) the average loss given default (from Altman and Suggitt, 2000), 3) the additional default rate induced by customer concentration (from Table 11), and 4) the average customer concentration for our sample firms.

Our back-of-the-envelope calculation suggests that customer concentration leads to around $4.7 million loss per loan.[13] More interestingly, Fig. 8 depicts the evolution of such losses in aggregate over time.[14] As customer concentration increases over the past two decades, it leads to increasing losses from loan failures, ranging from around $10 billion per year in the early-1990s to $50 billion per year in the mid-2000s.

Our loan failure analysis helps further explain why lenders impose costlier, stricter terms on loans offered to suppliers with concentrated customer bases, even though those suppliers themselves are more profitable.

9. Characteristics of customer–supplier relations

This section examines the channels through which major customers may trigger worse credit terms for supplier firms. We focus on three characteristics of major customers: financial distress, trade credit usage, and input specificity. Prior evidence suggests that when facing financially distressed customers, firms tend to grant deep concessions to maintain product market relationships (Wilner, 2000). Recent research also suggests that customers use trade credit to squeeze their suppliers, increasing the likelihood that these suppliers may not receive sufficient funds to meet their financial obligations (Murfin and Njoroge, 2014). Finally, as a firm produces more specific outputs that are tailored to the needs of their customers, they are more likely to be "held up" in the supply-chain relationship. In other words, as a customer purchases

[13] To be precise, we arrive at this number by multiplying average customer concentration 30%, the marginal effect from the loan failure estimate 0.25 (generated by estimates in column 2, Table 11), the loss given default 20% (from Altman and Suggitt, 2000), and the average loan face value $312 million.

[14] To estimate the aggregate loan losses at a certain point in time, we use the total face value of loans outstanding instead of the average face value, and then multiply the total face value, loss given default, the increase in default rate driven by customer concentration, and average customer concentration.

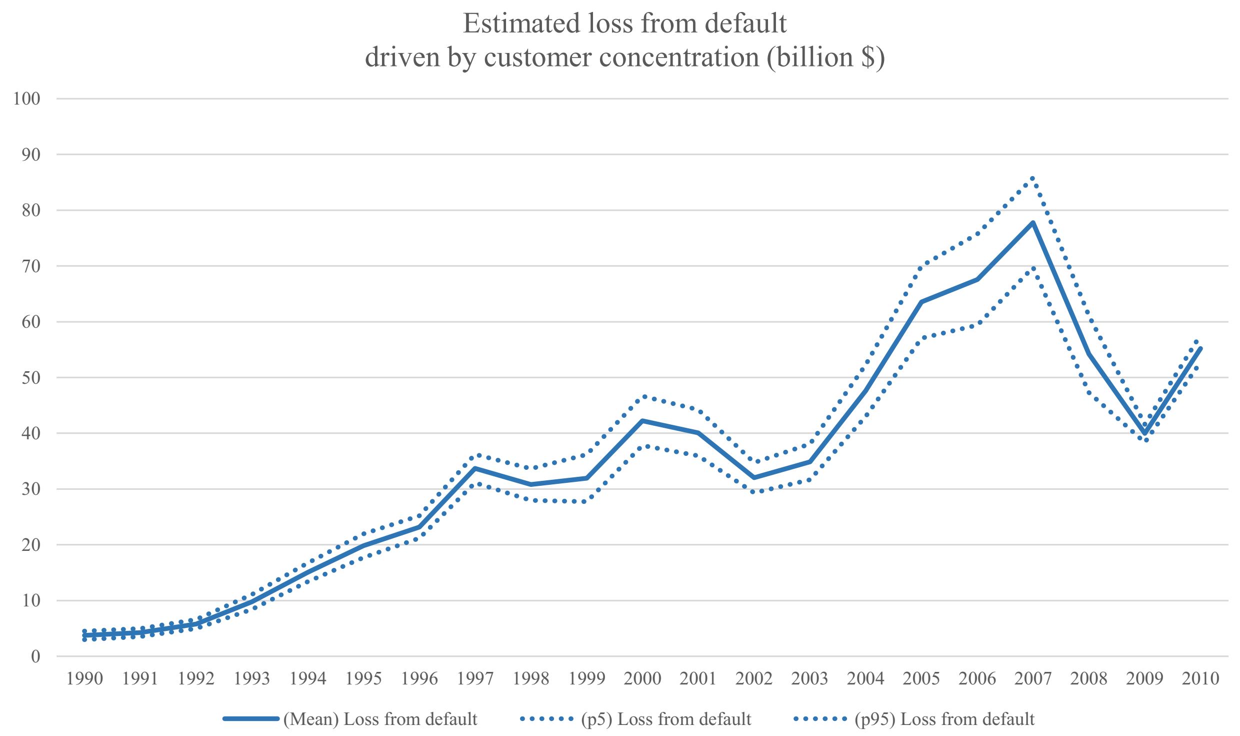

Fig. 8. Loss from default driven by customer concentration over time. This figure shows the estimated loss from loan failures over time in billion dollars. The solid line shows the estimated loss driven by the average concentration of borrowers' customer bases. The dotted lines show the 5% and 95% confidence intervals of such losses. Customer concentration is measured by *CustomerSales*.

specific products from a firm, the customer may become a more dominant buyer and thus has the power to bargain for more advantageous prices. According to existing research, one would expect a firm whose large customers are in worse financial shape, use more trade credit, and require specific inputs to receive worse loan terms from their banks. We examine those hypotheses in turn.

9.1. Customers' characteristics

9.1.1. Customers' financial condition

We design two measures of large customers' financial conditions. One measure is simply based on customers' leverage, while the other gauges customers' default probabilities. When a customer has a higher level of indebtedness, it may have difficulty maintaining existing purchase schedules or paying suppliers on time. These problems will be more relevant for suppliers when that customer is large. Accordingly, we construct a measure of customer financial condition that aggregates customers' leverage for each supplier. *CustomerLeverage* is defined as:

$$CustomerLeverage_i = \sum_{j=1}^{n_i} \%Sales_{ij} \times Leverage_j,$$

where $Leverage_j$ is the leverage of customer j. Higher values of *CustomerLeverage* indicate that the firm's large customers are more indebted.

Beyond measuring simple leverage ratios, we directly gauge customers' financial distress using their probability of default based on Merton (1974) model. We follow Bharath and Shumway (2008) and employ a reduced-form model to calculate customers' distance to default (*DD*). Higher distance to default indicates that a firm is less likely to default. For each supplier, we measure the average default likelihood of its major customers using its percentage sales to these customers and refer to this variable as *CustomerDefault*. The variable is defined as follows:

$$CustomerDefault_i = \sum_{j=1}^{n_i} \%Sales_{ij} \times (1 - DD_j),$$

where DD_j is the predicted distance to default for customer j, scaled by 100 so it is within the range of zero to one. Similar to *CustomerLeverage*, higher values of *CustomerDefault* indicate that the firm faces a more financially distressed customer base.

9.1.2. Depth of credit relations

We next consider the effect of customers' trade credit usage on the firm's credit terms. Anecdotal evidence and recent literature show that when large customers run high balances on accounts payable, their suppliers face liquidity shortages and even distress (see Murfin and Njoroge, 2014). We focus on the accounts payable of a firm's large customers, which account for the amount of purchases that these customers have not yet paid for. Accordingly, we measure large customers' trade credit usage as the sum of those customers' accounts payable weighted by their supplier firms' sales to large customers. We scale this accounts payable measure, alternatively, by a customer's total sales and cost of goods sold (COGS) to ensure that our results are not sensitive to the choice of scalars (see Garcia-Appendini and Montoriol-Garriga, 2013; Petersen and Rajan, 1997). Formally, we define *CustomerPayable* as:

$$CustomerPayable_i = \sum_{j=1}^{n_i} \%Sales_{ij} \times Payable_j,$$

where $Payable_j$ is the accounts payable of customer *j*, measured, alternatively, as the ratio of accounts payable to sales and the ratio of accounts payable to COGS. Higher values of *CustomerPayable* indicate that large customers tend to delay payments to their suppliers.

9.1.3. Relationship investments

Finally, we measure customers' input specificity using the industry-level input specificity as defined by Nunn (2007). Following Rauch (1999), Nunn (2007) designs an industry-level measure of input specificity according to whether an input is sold on an exchange, reference priced in a publication, or neither. In short, an input is considered to be "differentiated" if it is neither sold on an exchange nor reference priced. An alternative definition for input specificity is that the input is not sold on an exchange, in which case it is considered "non-homogeneous." Using the definition from Nunn (2007), we measure customers' input specificity as follows:

$$CustomerSpecificity_i = \sum_{j=1}^{n_i} \%Sales_{ij} \times Specificity_j,$$

where $Specificity_j$ is the input specificity of customer *j*'s industry. *Specificity* is defined as the proportion of differential inputs or non-homogeneous inputs used by a certain industry. Industries are classified according to the input and output of commodity flows by the Bureau of Economic Analysis in 1997. Higher values of *CustomerSpecificity* indicate the customers are likely to request more relationship-specific investments from their suppliers.

9.2. Results

We report the impact of customers' characteristics on firms' borrowing terms in Table 12, where we estimate models that resemble those of our baseline tests.[15] Columns 1 and 2 of Table 12 show the relation between loan spreads and customer financial condition measures, *CustomerLeverage* and *CustomerDefault*. Both measures attract significant, positive coefficients, suggesting that firms facing large, financially distressed customers experience significantly higher interest spreads on their new loans. Columns 3 and 4 show the relation between loan spreads and customers' demand of trade credit. The results suggest that banks extend costlier credit to firms whose customers tend to delay payments for their purchases. Finally, columns 5 and 6 show the relation between loan spreads and customers' input specificity. The results suggest that firms whose major customers require more relationship-specific investments observe a higher loan spread.

The results of this section are important in confirming the logic behind our base findings. A deeper relation with a small set of large customers has negative consequences for a firm's relations with its creditors, and more so the more financially unhealthy those customers are and the more bargaining power they have in terms of their trade and investment relations.

10. Changes in the competitive landscape

At the same time that customer-base concentration imposes growing financing costs onto U.S. firms, they face increasingly intense competition in their product markets. This is important for our study, as competition could be associated with customer-base consolidation, ultimately affecting suppliers' cost of borrowing. In this vein, Irvine and Pontiff (2009) show that global competition increases firm cash flow risk, and recent studies suggest that when facing the entry of foreign competitors, firms resort to conservative policies, such as larger cash holdings, lower R&D investments, and lower debt levels (see Fresard, 2010; Valta, 2012, and Fresard and Valta, 2015). Changes in competition can have a pervasive influence on the structure of supply-chain relations as well as firms' financial policies. In this section, we assess in detail the extent to which the relation between customer-base concentration and loan contract terms is influenced by the competitive environment.

10.1. Gauging the competitive environment

We first collect measures of product market competition from the Hoberg–Phillips Data Library. (Hoberg and Phillips, 2010a, 2015) measure "product similarity" among firms' product description in their 10-K reports, characterizing industries by grouping together firms of similar products (text-based industry classification, or TNIC). We collect the Herfindahl index of TNIC industries, *TNIC HHI*, which measures the intensity of competition that a firm faces from direct rivals. We also collect the "fitted Herfindahl index" of SIC industries, which is computed by taking into account information from both public and private firms [*Fitted HHI*, see Hoberg and Phillips, 2010b].

Importantly, the penetration of foreign goods into the U.S. has changed the competition dynamics of many industrial sectors (see, e.g., Bernard, Jensen, and Schott, 2006). In that context, we construct a measure of import penetration using U.S. import–export data from 1972–2005 compiled by Bernard, Jensen, and Schott (2006) and Schott (2008).[16] Following Irvine and Pontiff (2009), we calculate import penetration of an industry (classified on the four-digit SIC level) using the value of U.S. import of goods in that industry divided by the total shipment, excluding exports from the U.S. *Penetration* is defined as imports/(shipment – exports). We also gauge the threat of foreign entry using import tariff data over the 1992–2005 period, compiled by Feenstra (1996),Feenstra, Romalis, and Schott (2002), and Schott (2008). Following Fresard (2010) and Fresard and Valta (2015), we define "a large tariff cut" as a reduction

[15] Results on the duration and depth of bank relationships are omitted but are readily available. The same applies for estimations using IV and GMM approaches.

[16] The data we use can be found on Professor Peter Schott's website.

Table 12
Loan spreads and customer characteristics.
This table shows the relation between loan spreads and customer characteristics. The dependent variable is loan spreads. Column 1 shows the regression results for *CustomerLeverage*: the leverage of major customers, weighted by the firm's percentage sales to these customers. Column 2 shows the regression results for *CustomerDefault*: the inverse of the distance to default of major customers predicted by the KMV-Merton model, weighted by the firm's percentage sales to these customers. Column 3 shows the results for customers' weighted average accounts payable over sales. Column 4 shows the results for customers' accounts payable over cost of goods sold (COGS). Column 5 shows the results for customers' weighted average level of differentiated inputs. Column 6 shows the results for customers' weighted average level of non-homogeneous inputs. All regressions use industry-fixed effects and bank-fixed effects. Industry is classified as two-digit SIC industry and the lending banks are classified by their ultimate parents. Robust-clustered *t*-statistics are shown in parentheses. See Table 1 for sample descriptions and Appendix A for variable definitions.

Dep.var.: *LoanSpread*	*CustomerFinance* measured by		*CustomerPayable* measured by		*CustomerSpecificity* measured by	
	(1) *Leverage*	(2) *Distance-Default*	(3) *Payable/Sales*	(4) *Payable/COGS*	(5) *Differentiated input*	(6) *Non-homogeneous input*
CustomerFinance	150.92***	149.89*				
	(3.43)	(2.17)				
CustomerPayable			347.93**	188.44*		
			(2.02)	(1.77)		
CustomerSpecificity					52.32***	41.85***
					(3.15)	(2.66)
Size	−17.68***	−18.35***	−18.20***	−18.17***	−23.54***	−23.50***
	(−5.70)	(−5.74)	(−5.76)	(−5.76)	(−6.09)	(−5.98)
Age	−0.81***	−0.86***	−0.85***	−0.86***	−0.46	−0.49
	(−4.19)	(−4.16)	(−4.24)	(−4.18)	(−1.55)	(−1.61)
Profitability	−278.81***	−274.82***	−285.35***	−284.60***	−377.83***	−378.08***
	(−5.70)	(−5.63)	(−5.83)	(−5.82)	(−5.84)	(−5.76)
Tangibility	−7.32	−6.47	−0.11	0.23	−3.43	−2.16
	(−0.40)	(−0.35)	(−0.01)	(0.01)	(−0.11)	(−0.07)
M/B	−2.61	−4.07	−3.92	−3.93	2.75	2.79
	(−0.88)	(−1.33)	(−1.34)	(−1.36)	(0.73)	(0.75)
Leverage	122.54***	119.43***	120.21***	120.15***	125.36***	124.24***
	(7.74)	(7.74)	(7.67)	(7.54)	(5.11)	(4.98)
Ratings	40.60***	41.01***	43.23***	43.13***	50.31***	50.31***
	(4.75)	(4.85)	(5.07)	(5.08)	(5.47)	(5.41)
CreditSpread	83.23***	75.41**	84.54***	84.47***	83.84***	84.07***
	(2.71)	(2.44)	(2.71)	(2.71)	(2.66)	(2.68)
TermSpread	3.35	4.39	3.99	3.97	0.03	0.26
	(0.62)	(0.81)	(0.72)	(0.72)	(0.00)	(0.04)
GDPGrowth	−4.37	−4.99	−3.94	−4.01	−1.45	−1.44
	(−0.90)	(−1.00)	(−0.81)	(−0.83)	(−0.35)	(−0.35)
LoanMaturity	0.22	0.30**	0.21	0.21	−0.09	−0.09
	(1.46)	(2.03)	(1.35)	(1.34)	(−0.35)	(−0.36)
LoanSize	−16.56***	−15.53***	−16.35***	−16.10***	−10.71***	−10.33**
	(−5.42)	(−5.37)	(−5.45)	(−5.26)	(−2.60)	(−2.50)
LoanType	47.49***	49.10***	48.23***	48.35***	61.18***	61.32***
	(9.17)	(9.87)	(9.23)	(9.39)	(8.06)	(8.04)
Observations	2,903	2,770	2,770	2,903	870	833
R-squared	0.58	0.59	0.29	0.28	0.30	0.31

*** p-value$<$ 0.01,
** p-value$<$ 0.05,
* p-value$<$ 0.10.

in tariff in an industry that is larger than three times of the historical median tariff cut in that industry. We then define a dummy variable (*Tariff cut*) that equals one for a given year if a large tariff cut has occurred in the industry (classified at the four-digit SIC level).

10.2. Results

The tests that follow assess the extent to which the relation between customer-base concentration and loan contract terms is affected by the changing competitive landscape. We first examine whether the coefficient of *CustomerConcentration* in our estimations is influenced by industry competition measures. Table 13 reports the results from the regressions for *LoanSpread*. Columns 1 through 4 show results where we control for a firm's own product market competition, while columns 5 through 8 show results where we control for the competition faced by a firm's largest customer. We first control for the product market concentration in industries classified by product similarity (*TNIC HHI*), followed by the fitted industry concentration based on information from all public and private firms (*Fitted HHI*). We then control for import penetration (*Penetration*) and post-tariff-cut dummy (*Tariff cut*).

Across all specifications, *CustomerConcentration* attracts positive and significant coefficients, indicating that the effect of customer concentration is robust to controlling for product market competition and import penetration. Notably, the coefficient of *CustomerConcentration* varies in magnitude, with some aspects of competition (*Fitted HHI* and *Penetration*) enhancing the explanatory power of

Table 13
Competition, customer concentration, and loan spreads.
This table shows the relation between loan spreads and customer concentration, controlling for product market competition in both a firm's own industry and the firm's largest customer's industry. The dependent variable is loan spreads. Columns 1 through 4 show regression results controlling for a firm's own product market competition. Columns 5 through 8 control for the competition faced by a firm's largest customer. In columns 1 and 5, product market competition is measured by *TNIC HHI*, the Herfindahl index in text-based network industries. In columns 2 and 6, competition is measured by *Fitted HHI*, the fitted Herfindahl index in SIC industries using information from both public and private firms. In columns 3 and 7, the proxy for competition is *Penetration*, the import penetration in four-digit SIC industries. In columns 4 and 8, competition is measured by *Tariff cut*, an indicator for whether the industry (four-digit SIC) has experienced a large tariff cut. *CustomerConcentration* is measured by *CustomerSales*. All regressions use industry-fixed effects and bank-fixed effects. Industry is classified as two-digit SIC industry and the lending banks are classified by their ultimate parents. Robust-clustered *t*-statistics are shown in parentheses. See Table 1 for sample descriptions and Appendix A for variable definitions.

	Supplier's own industry				Customer's industry			
Dep.var.: *LoanSpread* *Competition* proxied by:	(1) *TNIC HHI*	(2) *Fitted HHI*	(3) *Penetration*	(4) *Tariff cut*	(5) *TNIC HHI*	(6) *Fitted HHI*	(7) *Penetration*	(8) *Tariff cut*
CustomerConcentration	34.14*	60.40***	40.59**	44.18**	32.09*	56.44***	78.42***	39.94**
	(1.88)	(3.68)	(1.97)	(2.39)	(1.67)	(3.26)	(3.94)	(2.25)
Competition	−6.62	−42.43	0.02	−5.41	−17.12	−25.24	8.61	14.04*
	(−0.39)	(−0.34)	(0.04)	(−0.86)	(−0.73)	(−0.38)	(0.93)	(1.87)
Size	−14.08***	−15.02***	−12.39***	−15.94***	−18.09***	−15.33***	−10.42**	−16.71***
	(−3.59)	(−4.73)	(−3.37)	(−5.17)	(−4.88)	(−4.88)	(−2.42)	(−5.35)
Age	−0.90***	−0.60**	−0.74**	−0.78***	−0.84***	−0.70***	−0.25	−0.74***
	(−4.53)	(−2.43)	(−2.03)	(−3.59)	(−3.92)	(−2.79)	(−0.60)	(−3.41)
Profitability	−149.05***	−139.36***	−83.86***	−143.62***	−135.63***	−139.76***	−123.03***	−142.59***
	(−6.49)	(−5.90)	(−3.26)	(−6.82)	(−6.32)	(−6.10)	(−3.72)	(−6.87)
Tangibility	−13.14	−44.40**	−46.80	−30.34*	−9.82	−57.11***	−70.99**	−38.01**
	(−0.78)	(−2.44)	(−1.59)	(−1.68)	(−0.52)	(−3.48)	(−2.16)	(−2.06)
M/B	−10.63***	−8.82***	−8.53***	−9.80***	−11.43***	−8.95***	−2.62	−9.52***
	(−3.14)	(−2.66)	(−3.05)	(−3.24)	(−3.25)	(−2.61)	(−0.59)	(−3.36)
Leverage	108.04***	125.10***	146.44***	112.68***	112.49***	116.64***	124.38***	113.55***
	(7.15)	(8.03)	(7.52)	(6.82)	(6.87)	(7.80)	(4.96)	(7.39)
Ratings	39.24***	28.55***	25.18***	39.35***	40.14***	26.98***	27.76***	39.70***
	(4.19)	(2.91)	(2.71)	(4.45)	(4.04)	(2.89)	(2.59)	(4.61)
CreditSpread	52.29	101.92***	107.93***	87.83***	57.73	89.47**	55.98	86.41***
	(1.45)	(2.99)	(3.30)	(2.60)	(1.46)	(2.50)	(1.20)	(2.59)
TermSpread	4.50	−0.15	−0.18	1.17	5.46	2.43	1.68	1.45
	(0.87)	(−0.02)	(−0.03)	(0.21)	(1.07)	(0.33)	(0.19)	(0.26)
GDPGrowth	−8.68	0.13	−0.34	−3.77	−8.36	1.30	−2.51	−4.04
	(−1.58)	(0.03)	(−0.08)	(−0.74)	(−1.40)	(0.28)	(−0.40)	(−0.80)
LoanMaturity	0.38**	0.24	0.13	0.20	0.38**	0.33**	0.19	0.20
	(2.25)	(1.50)	(0.67)	(1.32)	(2.20)	(2.10)	(0.75)	(1.30)
LoanSize	−19.53***	−17.85***	−16.60***	−17.44***	−18.71***	−15.80***	−16.95***	−17.05***
	(−5.80)	(−6.76)	(−5.20)	(−5.90)	(−4.84)	(−7.32)	(−5.87)	(−5.85)
LoanType	43.48***	47.69***	46.28***	47.93***	45.16***	46.64***	55.36***	48.06***
	(7.95)	(9.14)	(9.51)	(9.58)	(7.98)	(8.11)	(8.66)	(9.64)
Observations	2,409	2,237	1,389	2,997	2,503	2,201	965	2,997
R-squared	0.59	0.58	0.55	0.57	0.59	0.58	0.50	0.57

*** p-value$<$ 0.01,
** p-value$<$ 0.05,
* p-value$<$ 0.10.

customer-base concentration, while others (*TNIC HHI*) attenuating that effect.

We go a step further in our analysis and investigate the joint determination between industry competition, customer concentration, and loan contract terms. Following the 3SLS framework outlined in Eq. (6), we estimate a system of three equations, taking into account that the competitive environment in the product market and a firm's customer concentration can be interdependent and that both can affect a firm's cost of borrowing. Table 14 presents the results from the 3SLS estimation. Panel A reports results where we measure product market concentration using *TNIC HHI* and *Fitted HHI*, and Panel B reports results where we use *Penetration* and *Tariff cut* as proxies for competition. Across all specifications, *CustomerConcentration* retains a significant positive coefficient in models for *LoanSpread*.

In all, our results suggest that the competitive environment of the industry — though important in influencing firms' borrowing costs — may not subside the observed negative relation between customer concentration and loan markups.

11. Concluding remarks

Recent literature argues that customer concentration can increase firms' operational efficiency, leading to significant increases in profitability. While recognizing and verifying the existence of those gains, we examine the potential costs associated with deeper relationships between suppliers and customers.

Our study looks at how credit markets respond to customer-base concentration. It does so examining the credit terms offered by banks. Using detailed information

Table 14
Industry competitive environment, customer concentration, and loan spreads, 3SLS estimation.
This table shows the results from 3SLS estimation for loan spreads, customer concentration, and the product market competition. In Panel A of this table, columns 1 through 3 show the results where competition is proxied by *TNIC HHI* and columns 4 through 6 show the results where competition is proxied by *Fitted HHI*. In Panel B, columns 1 through 3 show the results where competition is proxied by *Penetration* and columns 4 through 6 show the results where competition is proxied by *Tariff Cut*. *CustomerConcentration* is measured by *CustomerSales*. All regressions use industry-fixed effects and bank-fixed effects. Industry is classified as two-digit SIC industry and the lending banks are classified by their ultimate parents. Robust *z*-statistics are shown in parentheses. See Table 1 for sample descriptions and Appendix A for variable definitions.

Panel A

	Competition is *TNIC HHI*			*Competition* is *Fitted HHI*		
Dep. var.:	(1) *LoanSpread*	(2) *Competition*	(3) *CustomerConcentration*	(4) *LoanSpread*	(5) *Competition*	(6) *CustomerConcentration*
LoanSpread		−0.01	0.01***		−0.01***	0.01***
		(−0.60)	(11.02)		(−6.85)	(9.76)
CustomerConcentration	211.34***	0.10*		204.23***	0.14***	
	(11.05)	(1.94)		(10.00)	(23.35)	
Competition	4.29		0.20**	−871.29***		6.06***
	(0.16)		(2.48)	(-5.75)		(22.49)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,396	2,396	2,396	2,223	2,223	2,223
R-squared	0.32	−0.14	−0.90	0.24	−1.68	−1.27

Panel B

	Competition is *penetration*			*Competition* is *tariff cut*		
Dep. var.:	(1) *LoanSpread*	(2) *Competition*	(3) *CustomerConcentration*	(4) *LoanSpread*	(5) *Competition*	(6) *CustomerConcentration*
LoanSpread		0.01***	0.01***		−0.01	0.01***
		(3.65)	(5.82)		(−0.33)	(5.17)
CustomerConcentration	129.76***	−9.09***		124.57***	2.32***	
	(5.98)	(-8.42)		(5.77)	(23.35)	
Competition	3.92***		−0.03***	−2.00		0.31***
	(3.04)		(−8.41)	(−0.27)		(24.08)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,378	1,378	1,378	2,983	2,983	2,983
R-squared	0.38	−0.69	−0.64	0.37	−0.62	−0.34

*** p-value < 0.01,
** p-value < 0.05,
* p-value < 0.10.

on bank loans, we study how customer-base concentration affects a firm's borrowing terms, including loan interest spread, maturity, and the number of restrictive covenants. We further gauge the impact of customer profile on the length and intensity of suppliers' relations with their banks. Our tests show that higher levels of customer concentration generally increase the interest rates and the number of restrictive covenants on a firm's bank loans. Customer concentration also reduces loan maturities and the duration and depth of banking relationships.

Exploring the cross-sectional variation in customer characteristics, we further show that when firms have larger, more financially distressed customers, they face even worse loan terms. We also show direct evidence that a more concentrated customer base affects a firm's credit risk. In particular, suppliers with higher customer concentration and more financially troubled customers are more likely to default on their loans. This result corroborates the argument that while customer concentration may make supply-chain relations more efficient and profitable, a deeper exposure to a small set of large customers has negative consequences for the firm's relations with its creditors.

Understanding the trade-offs associated with customer concentration is important as the modern business-to-business economy experiences increasing levels of concentration and supply-chain integration. Integration along the supply chain is fraught with contracting problems between customers and suppliers. These problems allow powerful customers to set trade terms to their own advantage, while leaving suppliers "held-up" due to costly, relationship-specific investments they may be forced to make. Our paper sheds light on one additional cost induced by this contracting problem. This phenomenon is reflected in the increased borrowing costs and tightened debt contract terms required by banks. Future research would benefit from understanding how bank contracting can complement or substitute for supply-chain contracting. Overall, our analyses suggest that the cost related to customer concentration deserves better understanding and may give new insights into important research topics, such as the issue of optimal concentration, integration along the productive supply chain, and the limits of the modern corporation.

Appendix A. Variable definitions

LoanSpread: All-in-drawn loan spread over LIBOR
LoanCovenants: Total number of covenants on the loan package
LoanMaturity: Loan maturity in months
FutureLoans: The total dollar amount of loans issued by the same bank in the future, scaled by the current loan amount
FutureDuration: The number of months until the last loan extended by the same bank
CustomerSales: Total percentage sales to all major customers
CustomerSize: Total size of all major customers, weighted by the firm's percentage sales to customer
CustomerLeverage: Leverage of major customers, weighted by the firm's percentage sales to customer
CustomerDefault: The inverse distance to default (1-distance to default) of major customers predicted by Bharath and Shumway (2008) distance-to-default model, weighted by the firm's percentage sales to customer
CustomerPayable: Accounts payable of major customers, weighted by the firm's percentage sales to the customers. Accounts payable are measured scaled both by customers' sales and COGS
CustomerSpecificity: The level of input specificity by the industries of major customers, weighted by the firm's percentage sales to the customers. Input specificity is measured by both the percentage of non-homogeneous goods used by an industry and the percentage of differentiated goods used by an industry (Nunn, 2007)
Size: Log of total assets (AT)
Age: Years after a firm's first appearance in Compustat database
Profitability: Operating income (OIBDP)/total assets
Tangibility: Property, plant, and equipment (PPENT)/total assets
M/B: (Stock price (PRCC) × shares outstanding (CSHO) + total assets – book equity (CEQ))/total assets
Leverage: (Long-term debt (DLTT) + current debt (DLC))/total assets
Ratings: A dummy variable that equals one if the firm has a bond rating, zero otherwise
CreditSpread: Yield spread between average AAA-rated corporate bonds and average BBB-rated corporate bonds
TermSpread: Yield spread between 10-year Treasury bond and 3-month Treasury bills
GDPGrowth: Quarterly average of GDP growth rate of the year
LoanSize: Log of total loan amount (in dollars)
LoanType: A dummy variable that equals one if the loan is a term loan, zero if loan is a revolver

Appendix B

Table B.1
Loan spreads and alternative measures of customer concentration.
This table shows the relation between loan spreads and alternative measures of customer concentration. The dependent variable is All-in-drawn loan spread (*LoanSpread*). All regressions use industry-fixed effects and bank-fixed effects. Industry is classified as two-digit SIC industry and the lending banks are classified by their ultimate parents. Robust-clustered *t*-statistics are shown in parentheses. *CustomerSales* is the sum of the percentage sales to the set of customers a firm reports as "major customers." *CustomerSize* is the total size of all major customers, weighted by the firm's percentage sales to these customers. *CustomerHHI* is measured as the sum of squared percentage sales to major customers; *CustomerGini* is the Gini coefficient of a firm's sales to its customers; *CustomerMax* is the highest percentage sales to major customers; and *CustomerCount* is the total number of a firm's major customers. See Appendix A for variable definitions.

	CustomerConcentration is:					
Dep. var.: *LoanSpread* Measure of concentration:	(1) *CustomerSales*	(2) *CustomerSize*	(3) *CustomerHHI*	(4) *CustomerGini*	(5) *CustomerMax*	(6) *CustomerCount*
CustomerConcentration	40.89***	5.28***	72.99***	7.38**	53.10*	6.55*
	(3.32)	(3.72)	(5.12)	(2.14)	(1.83)	(1.96)
Size	−17.69***	−17.97***	−17.60***	−17.42***	−18.18***	−17.61***
	(−5.40)	(−5.43)	(−6.68)	(−6.01)	(−6.93)	(−6.39)
Age	−0.60***	−0.61***	−0.78***	−0.82***	−0.85***	−0.82***
	(−2.88)	(−3.07)	(−3.77)	(−4.04)	(−4.33)	(−4.05)
Profitability	−246.94***	−273.44***	−257.76***	−260.61***	−263.00***	−261.58***
	(−3.89)	(−4.23)	(−3.96)	(−3.99)	(−3.71)	(−3.87)
Tangibility	−27.66	−22.23	−8.96	−3.84	−0.02	−3.34
	(−0.77)	(−0.62)	(−0.42)	(−0.17)	(−0.00)	(−0.14)
M/B	−3.75	−1.83	−4.99	−4.96	−4.93	−4.96
	(−0.90)	(−0.40)	(−1.55)	(−1.56)	(−1.44)	(−1.53)
Leverage	128.86***	131.47***	122.48***	120.42***	117.93***	120.01***
	(8.49)	(8.21)	(10.84)	(10.68)	(9.90)	(10.27)

(*continued on next page*)

Table B.1 (*continued*)

	CustomerConcentration is:					
Dep. var.: *LoanSpread*	(1)	(2)	(3)	(4)	(5)	(6)
Measure of concentration:	*CustomerSales*	*CustomerSize*	*CustomerHHI*	*CustomerGini*	*CustomerMax*	*CustomerCount*
Ratings	35.74***	35.24***	41.52***	41.93***	42.92***	42.36***
	(4.68)	(4.62)	(6.96)	(6.95)	(7.77)	(7.17)
CreditSpread	81.53***	76.32***	88.35***	89.42***	88.03***	89.36***
	(5.49)	(4.97)	(6.43)	(6.49)	(6.35)	(6.45)
TermSpread	3.40	4.42*	2.49	2.66	2.65	2.64
	(1.31)	(1.69)	(1.27)	(1.36)	(1.33)	(1.33)
GDPGrowth	−4.79*	−5.18**	−3.96	−3.67	−4.14	−3.74
	(−1.96)	(−2.08)	(−1.65)	(−1.55)	(−1.68)	(−1.57)
LoanMaturity	5.91	6.48	8.18*	7.99*	8.01*	8.02*
	(1.50)	(1.61)	(1.88)	(1.83)	(1.78)	(1.83)
LoanSize	−15.77***	−16.02***	−16.04***	−15.67***	−15.74***	−15.71***
	(−5.66)	(−5.69)	(−6.65)	(−6.45)	(−6.41)	(−6.45)
LoanType	45.78***	44.87***	48.80***	49.04***	48.93***	49.05***
	(6.86)	(6.76)	(7.07)	(7.06)	(7.05)	(7.04)
Observations	2,983	2,983	2,983	2,983	2,983	2,983
R-squared	0.61	0.62	0.57	0.57	0.57	0.57

*** p-value$<$ 0.01,
** p-value$<$ 0.05,
* p-value$<$ 0.10.

References

Ahern, K., Harford, J., 2014. The importance of industry links in merger waves. Journal of Finance 69, 527–576.
Allen, J., Phillips, G., 2000. Corporate equity ownership, strategic alliances, and product market relationships. Journal of Finance 55, 2791–2815.
Altman, J., Suggitt, H., 2000. Default rates in the syndicated bank loan market: a mortality analysis. Journal of Banking & Finance 24, 229–253.
Andrade, G., Mitchell, M., Stafford, E., 2001. New evidence and perspectives on mergers. Journal of Economic Perspectives 15, 103–120.
Asker, E., Ljungqvist, A., 2010. Competition and the structure of vertical relationships in capital markets. Journal of Political Economy 118, 599–647.
Banerjee, S., Dasgupta, S., Kim, Y., 2008. Buyer-supplier relationships and the stakeholder theory of capital structure. Journal of Finance 63, 2507–2552.
Bernard, A.B., Jensen, B., Schott, P., 2006. Trade costs, firms and productivity. Journal of Monetary Economics 53, 917–937.
Bharath, S., Shumway, T., 2008. Forecasting default with the merton distance to default model. Review of Financial Studies 21, 1339–1369.
Bhattacharyya, S., Nain, A., 2011. Horizontal acquisition and buying power: a product market analysis. Journal of Financial Economics 99, 97–115.
Bolton, P., Scharfstein, D., 1998. Corporate finance, the theory of the firm, and organizations. Journal of Economic Perspectives 12, 95–114.
Bruner, R.F., 2004. Applied Mergers and Acquisitions. John Wiley & Sons, Inc., Hoboken, NJ.
Campello, M., Lin, C., Ma, Y., Zou, H., 2011. The real and financial implications of corporate hedging. Journal of Finance 66, 1615–1647.
Cen, L., Dasgupta, S., Elkamhi, R., Pungaliya, R., 2015. Reputation and loan contract terms: the role of principal customers. Review of Finance 14, 1–33.
Chava, S., Jarrow, R., 2004. Bankruptcy prediction with industry effects. Review of Finance 8, 537–569.
Chava, S., Roberts, M., 2008. How does financing impact investment? the role of debt covenants. Journal of Finance 63, 2085–2121.
Chava, S., Stefanescu, C., Turnbull, S., 2011. Modeling the loss distribution. Management Science 57, 1267–1287.
Cohen, L., Frazzini, A., 2008. Economic links and predictable returns. Journal of Finance 63, 1977–2011.
Erel, I., Jang, Y., Weisbach, M.S., 2015. Do acquisitions relieve target firms' financial constraints? Journal of Finance 70, 289–328.
Fee, E., Thomas, S., 2004. Sources of gains in horizontal mergers: evidence from customer, supplier, and rival firms. Journal of Financial Economics 74, 423–460.
Feenstra, R.C., 1996. U.s. imports, 1972–1994, data and concordances. In: NBER Working Paper No. 5515.
Feenstra, R.C., Romalis, J., Schott, P., 2002. U.s. imports, exports and tariff data, 1989–2001. In: NBER Working Paper No. 9387.
Fresard, L., 2010. Financial strength and product market behavior: the real effects of corporate cash holdings. Journal of Finance 65, 1097–1122.
Fresard, L., Valta, P., 2015. How does corporate investment respond to increased entry threat? Review of Corporate Finance Studies 5, 1–35.
Garcia-Appendini, E., Montoriol-Garriga, J., 2013. Firms as liquidity providers: evidence from the 2007–2008 financial crisis. Journal of Financial Economics 109, 272–291.
Giannetti, M., Burkart, M., Ellingsen, T., 2011. What you sell is what you lend? explaining trade credit contracts. Review of Financial Studies 24, 1261–1298.
Graham, J.R., Li, S., Qiu, J., 2008. Corporate misreporting and bank loan contracting. Journal of Financial Economics 89, 44–61.
Hall, B., Jaffe, A., Trajtenberg, M., 2001. The NBER patent citations data file: lessons, insights and methodological tools. In: NBER Working Paper, No. 8498.
Hart, O., 1995. Firms, Contracts, and Financial Structure. Oxford University Press, New York.
Haushalter, D., Klasa, S., Maxwell, W., 2007. The influence of product market dynamics on a firm's cash holdings and hedging behavior. Journal of Financial Economics 84, 797–825.
Hertzel, M., Officer, M., 2012. Industry contagion in loan spreads. Journal of Financial Economics 103, 493–506.
Hoberg, G., Phillips, G., 2010a. Product market synergies and competition in mergers and acquisitions: a text-based analysis. Review of Financial Studies 23, 3773–3811.
Hoberg, G., Phillips, G., 2010b. Real and financial industry booms and busts. Journal of Finance 65, 45–86.
Hoberg, G., Phillips, G., 2015. Text-based network industries and endogenous product differentiation. Journal of Political Economy. Forthcoming.
Irvine, P., Park, S., Yildizhan, C., 2014. Customer-base concentration, profitability and distress across the corporate life cycle. Texas Christian University and University of Georgia. Unpublished working paper.
Irvine, P.J., Pontiff, J., 2009. Idiosyncratic return volatility, cash flows, and product market competition. Review of Financial Studies 22, 1149–1177.
Itzkowitz, J., 2013. Customers and cash: how relationships affect suppliers' cash holdings. Journal of Corporate Finance 19, 159–180.
Kale, J., Shahrur, H., 2007. Corporate capital structure and the characteristics of suppliers and customers. Journal of Financial Economics 83, 321–365.
Kelly, B., Lustig, H., Van Nieuwerburgh, S., 2013. Firm volatility in granular networks. In: NBER Working Paper, No. 19466.
Kolay, M., Lemmon, M., Tashjian, E., 2016. Spreading the misery? sources of bankruptcy spillover in the supply chain. Journal of Financial and Quantitative Analysis. Forthcoming.

Lin, C., Ma, Y., Malatesta, P., Xuan, Y., 2011. Ownership structure and the cost of corporate borrowing. Journal of Financial Economics 100, 1–23.

Merton, R., 1974. On the pricing of corporate debt: the risk structure of interest rates. Journal of Finance 29, 449–470.

Murfin, J., Njoroge, K., 2014. The implicit costs of trade credit borrowing by large firms. Review of Financial Studies 28, 112–145.

Nunn, N., 2007. Relationship-specificity, incomplete contracts, and the pattern of trade. Quarterly Journal of Economics 122, 569–600.

Ovtchinnikov, A., 2013. Merger waves following industry deregulation. Journal of Corporate Finance 21, 51–76.

Patatoukas, P.N., 2012. Customer-base concentration: implications for firm performance and capital markets. The Accounting Review 87, 363–392.

Petersen, M., Rajan, R., 1997. Trade credit: theories and evidence. Review of Financial Studies 10, 661–691.

Rauch, J., 1999. Networks versus markets in international trade. Journal of International Economics 48, 7–35.

Roberts, M.R., Sufi, A., 2009. Renegotiation of financial contracts: evidence from private credit agreements. Journal of Financial Economics 93, 159–184.

Schoenberg, R., Reeves, R., 1999. What determines acquisition activity within an industry? European Management Journal 17, 93–98.

Schott, P.K., 2008. The relative sophistication of chinese exports. Economic Policy 23, 5–49.

Shleifer, A., Vishny, R., 1992. Liquidation values and debt capacity: a market equilibrium approach. Journal of Finance 47, 1343–1366.

Titman, S., 1984. The effect of capital structure on a firm's liquidation decision. Journal of Financial Economics 13, 137–151.

Titman, S., Wessels, R., 1988. The determinants of capital structure choice. Journal of Finance 43, 1–19.

Valta, P., 2012. Competition and the cost of debt. Journal of Financial Economics 105, 661–682.

Wilner, B., 2000. The exploitation of relationships in financial distress: the case of trade credit. Journal of Finance 55, 153–178.