# Customer Risk and The Choice Between Cash and Bank Credit Lines *

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**Abstract**

I use a matched buyer-supplier sample of U.S. industrial firms to investigate the impact of customer risk on suppliers' choice between cash and lines of credit as a source of liquidity. I find that customer risk decreases the reliance on bank-managed liquidity insurance relative to cash. This effect appears to be economically significant compared to previously documented factors affecting the choice between cash and lines of credit. Suppliers with high customer risk also appear to pay a higher cost for new credit lines and to be subject to more non-financial covenants. These results are consistent with the hypothesis that customer-supplier relationships can significantly shape corporate financial decisions.

**JEL:** G32

**Keywords:** Customer risk, lines of credit, cash management

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# 1 Introduction

Corporate liquidity management has long drawn the attention of both corporate finance academics and practitioners. Survey-based studies (see Lins *et al.*, 2010, and Campello *et al.*, 2011 and 2012) show that, in practice, cash and lines of credit are two essential components of a firm's cash management policy. Sufi (2009), Demiroglu and James (2010) and Acharya *et al.* (2013), among others, suggest that firms hold bank credit lines as substitutes for internal cash reserves. These studies highlight that operating performance, cash-flow variability, and aggregate risk are the key determinants of firms' choices between these two sources of liquidity.

In this paper, I focus on customer risk as a determinant of the choice between cash and lines of credit as sources of liquidity. I find that supplier firms facing higher risk on the customer side of their activities should shy away from revolving credit facilities and hold relatively more cash. The underlying rationale is that customer risk increases the cost of bank credit lines, either through tighter contractual terms (e.g. higher spread, shorter maturity) or a higher threat of covenant violation. The aim of this study is to shed further light on the crucial role of customer-supplier relationships in determining firms' financing decisions.

Starting with Titman (1984) and Titman and Wessels (1988), an entire stream of literature has long developed and investigated the idea that conditions on the product market can shape corporate financing policies[1]. Most of these studies, however, focus primarily on capital structure choices. Moreover, the existing liquidity management literature has also often left aside the potential effect of customer-supplier relationships on how firms choose to meet their liquidity needs. However, recent empirical evidence suggests that supplier firms' performance, risk and costs of financing are not neutral to customer-related risks, whether it be to the extreme case of default at the customer level (Hertzel *et al.*, 2008) or to customer-base concentration (Dhaliwal *et al.*, 2015). In addition, the existing trade credit literature highlights how supplier firms are likely to act as substitute credit providers for their suppliers (see Burkart and Ellingsen, 2004, or Tirole, 2006, for example) and how external financing, especially credit lines (Petersen and Rajan, 1997), is used to meet mechanically generated liquidity needs. Reconciling these two streams of literature to the existing research on lines of credit (Sufi, 2009, Acharya *et al.*, 2013, among others) suggests the existence of a relationship, regardless of its nature, between customer risk and the choice between cash and lines of credit.

The recent financial crisis provides concrete examples of such a link between financing decisions and customer risk. For example, the generalized failure of Chrysler, Ford and

[1]See also Poitevein (1989), Banerjee, Dasgupta and Kim (2008) and Hennessy and Livdan (2009) for further theoretical work and Kale and Shahrur (2007), Matsa (2011) or Hoberg, Phillips and Prabhala (2014), among others, for recent empirical evidence.

General Motors at the end of the 2000s generated turmoil for most of their suppliers, which suffered from a sudden impairment of their access to liquidity, even before recording effective operating losses. In particular, reports of banks "refusing to extend credit to parts makers who do lots of business with GM, Ford or Chrysler"[2] or "[cutting] back credit lines extended to [auto-part makers]"[3] were not uncommon between 2008 and 2010. Despite their anecdotal nature, these pieces of evidence further emphasize how doing business with potentially distressed large customers might shape financing decisions at the supplier firm level.

In this study, I rely on the Loan Pricing Corporation's (LPC) Dealscan database to build a comprehensive sample of credit line initiations for a sample of Compustat U.S. industrial firms, from 1987 to 2013. I also use customer data available from the Compustat Segment File to build a matched sample of LPC-Dealscan suppliers and their major corporate customers. I follow Sufi (2009) and Acharya *et al.* (2013) to measure credit line availability at the supplier firm level. Customer risk is defined, for each supplier firm, as the weighted average expected probability of default of all identified customers'.

My results show that higher customer risk is associated with a lower reliance on bank lines of credit as a source of liquidity. This effect is robust to explicitly controlling for previously documented determinants, as well as for a supplier's ability to collect pending invoices, which proxies for a crucial risk stemming from supplier-customer relationships. Quantitatively, my findings suggest that a one-standard-deviation increase in customer risk is associated with a significant decrease of between 1.48% up to 2.44% in the ratio of available lines of credit to total available liquidity. To put this in perspective, a one-standard-deviation decrease in past realized operating profitability is associated with, at worst, a 1.9% decrease in the credit lines ratio (the effect varies depending on regression model employed). These results highlight the importance of customer risk relative to operating performance, with respect to corporate cash management decisions. I further perform a 2SLS instrumental variables analysis to ensure that these results are not driven by omitted variables, especially at the bank level. I rely on two IVs that are idiosyncratic to customer firms and restrict my sample to supplier firms that do not share the same lead bank on any of their outstanding loans, with any of their customers. This analysis still indicates a lower reliance on lines of credit as a source of liquidity for firms with high customer risk.

In the second part of my analysis, I study the effect of customer risk on various dimensions of the cost of lines of credit. I first document a positive correlation between customer risk and the spread paid on new lines of credit, which implies that the risk of losing a

[2]"Bankruptcy Fears Grip Auto-Parts Suppliers", *The Wall Street Journal*, January 26$^{\text{th}}$ 2009

[3]"The Auto Industry's Other Crisis", *Businessweek*, March 13$^{\text{th}}$ 2009

substantial portion of revenues is explicitly priced by banks when granting supplier firms access to a "pre-committed" source of funds. Higher customer risk, however, does not appear to be associated with a greater number of covenants attached to credit line agreements. My findings indicate a mixed and weakly negative effect of customer risk on the number of performance-based covenants, and suggest that this effect is concentrated among small firms with low operating performance. These results are likely to reflect the "relative importance of future cash flows versus collateral in repaying a line of credit" reported in Flannery and Wang (2011) or, in a similar vein, the difference between performance and capital covenants, as presented in Aghion and Bolton (1992) or Christensen and Nikolaev (2011), among others. On the one hand, when lending to weaker firms with lower financial ratios, banks are likely to focus primarily on the underlying collateral (e.g. inventories or account receivables), or non-operating cash flows, to ensure repayment and thus assign less importance to restrictive covenants. On the other hand, cash flows may be an important component of expected repayment for financially healthy firms exhibiting higher operating performance. Were cash flows to fall short of expectations, financial covenants would then allow the lender to re-negotiate the terms of a loan agreement. Consistently, I find that banks impose a higher number of non-financial covenants (*i.e.* borrowing base provision, dividend restrictions, asset and equity sweeps, and debt sweeps) on firms with high customer risk and low operating cash flows.

I also perform additional tests to ensure the robustness of my results to several potential endogeneity issues. In particular, I implement a propensity score matched sample approach, which controls for all the observables relied on in this paper, as well as the cash and leverage ratios. The results of this analysis remain consistent with my predictions, and indicate a lower reliance on lines of credit as a source of liquidity, as well as a higher cost of bank credit lines, for firms with high customer risk. Additionally, this analysis shows that variations in the reliance on lines of credit do not solely reflect different capital structure choices. Altogether, these results strengthen the idea that customer risk is another key determinant of corporate liquidity management policies.

This paper contributes to two areas of the corporate finance literature. First, the results contribute to a better understanding of corporate cash management decisions, namely the choice between internal and external "pre-committed" sources of funds[4] (i.e. cash and lines of credit, respectively). Sufi (2009) finds that lines of credit are used primarily by large, mature, profitable firms with steady cash flows. Acharya *et al.* (2013) further show that high exposure to systematic risk both increases the cost of available lines of credit, and reduces the reliance on lines of credit as a source of liquidity. My results complement and extend this research by showing that buyer-induced risk leads to firms shying away from

[4]Itzkowitz (2013) studies the effect of customer-base concentration on cash holdings at the supplier level, and Garcia-Appendini and Montoriol-Garriga (2013) focus on suppliers as liquidity providers during the financial crisis. These studies, however, do not analyze the trade-off between cash and lines of credit.

credit lines, and increases the cost of bank liquidity, even after controlling for previously documented sources of risk.

Additionally, this study adds to the growing body of literature that investigates how corporate decisions are shaped by strategic interactions between a supplier firm and its customers. Titman (1984) theorizes that capital structure can mitigate agency conflicts between suppliers and customers, by forcing a supplier firm to implement a liquidation policy that maximizes the wealth of all its stakeholders. Low leverage then arises as mechanism to demonstrate commitment to a firm's buyers. Consistently, Titman and Wessels (1988) and Banerjee *et al.* (2008) find that firms with unique or specialized products have relatively lower debt ratios. Similarly, Kale and Shahrur (2007) find that firms relationship-specific investments are negatively correlated with leverage. More recently, Hoberg, Phillips and Prabhala (2014) provide evidence regarding product market conditions and their impact on cash holdings and payout decisions. In addition, Hertzel *et al.* (2008) and Kolay *et al.* (2015) study how distress at the customer level can impact supplier firms, and show negative wealth effects at the supplier level. Fee and Thomas (2004) and Brown *et al.* (2009) focus on the effect of customer-base concentration on the relative bargaining power of suppliers and customers. Cen et al. (2016) further document how the implicit certification resulting from maintaining a relationship with one or more principal customers allows supplier firms to obtain less restrictive terms on bank loans. Dhaliwal *et al.* (2015) and Demirci (2015) are the most recent attempts at empirically examining the effect of customer risk. Dhaliwal *et al.* (2015) focus on the supplier firm's cost of equity. Demirci (2015) studies the effect of customer risk on capital structure at the supplier firm level. In addition, this paper further differs from Demirci (2015) in how customer risk is proxied. While I rely on explicit measures of a customer's probability of default, Demirci (2015) measures customer risk using customers' credit ratings, return volatility or industry-adjusted book leverage.

The remainder of this paper is organized as follows. Section 2 presents the main hypotheses linking customer risk to the choice between cash and lines of credit. Section 3 describes the construction of the main sample and variables on which this study relies. Section 4 reports my main empirical findings. Section 5 presents various robustness tests, while Section 6 contains concluding remarks.

## 2 Hypothesis Development

Since Keynes (1936), it has been widely understood that liquidity is crucial for firms to ensure the continuity of their business. In the presence of market frictions (agency conflicts, asymmetric information, transaction costs, etc.), firms cannot freely turn to capital markets for financing and thus need to hold some form of liquidity. Consistently, a large body of the financial literature focuses on cash as a liquidity buffer[5] in the presence of imperfect markets. More recently, using bank lines of credit as an alternative source of liquidity has received increasing attention, both theoretical and empirical[6].

The use of revolving credit facilities provides borrowing firms with both greater financial flexibility and capacity to meet their liquidity needs. On the one hand, lines of credit allow firms to seize investment opportunities without burning cash or raising external capital in good states of nature (Lins, Servaes and Tufano, 2010). On the other hand, borrowing firms can use lines of credit as insurance against liquidity shocks (Holmstrom and Tirole, 1998, Thakor, 2005), especially to ensure the continuity of their activities in the midst of a financial crisis (Ivashina and Sharfstein, 2010, Campello, Giambona, Graham and Harvey, 2011 and 2012, Berrospide and Meisenzahl, 2015).

As such, credit lines appear to be a credible and potentially valuable substitute for cash as a source of liquidity. Yet, they can only serve as an imperfect substitute for cash, as noted by Demiroglu and James (2011) or Acharya, Almeida and Campello (2013). Declines in the borrower's operating performance might trigger the violation of one or several covenants attached to a credit line agreement. Such violations have been shown to significantly decrease a firm's debt capacity (Roberts and Sufi, 2009), restrict future firm decision-making and even lead to higher management turnover (Nini, Smith and Sufi, 2012). In addition, as highlighted in Acharya *et al.* (2013), lenders (*i.e.,* banks or financial institutions) might not be able to provide liquidity at all times. This could be the case following a global liquidity shock, such as the recent financial crisis. There thus exists a trade-off between cash and lines of credit as sources of liquidity. In other words, firms are more likely to rely on revolving credit facilities when the benefits of doing so (i.e., financial flexibility, liquidity insurance) outweigh the associated costs.

Sufi (2009) suggests that the threat of covenant violation is one of the main costs associated with lines of credit. As a consequence, a firm's operating performance is a key determinant of both accessing and maintaining a line of credit. Similarly, Acharya, Almeida, Ippolito and Perez (2014) document the effect of lines of credit covenant violations and show that such events lead to both a reduction in the size of existing lines of credit and stricter contractual terms on future lines of credit (e.g., higher spreads, lower maturities). Acharya, Almeida and Campello (2013) further investigate corporate cash

[5]See Opler *et al.* (1999), Almeida, Campello and Weisbach (2004), Faulkender and Wang (2006), or Acharya, Almeida and Campello (2007), among others.

[6]For theoretical evidence, see Holmstrom and Tirole, 1998, Thakor, 2005, Acharya, Almeida and Campello, 2013. Empirical evidence on the reliance on credit lines as a source of liquidity can be found in Sufi, 2009, Lins, Servaes and Tufano, 2010, Campello, Giambona, Graham and Harvey, 2011 and 2012, Acharya Almeida and Campello, 2013, Disatnik, Duchin and Schmidt, 2014, or Acharya, Almeida, Ippolito and Perez, 2014

management decisions through a model linking aggregate risk to the choice between cash and lines of credit. Their model suggests that firms with greater exposure to aggregate risk rely more heavily on cash. Similarly, bank lines of credit are explicitly more expensive for riskier firms, either through higher spreads or shorter maturities. These studies shed light on both the direct costs (which are contracted upon) and the underlying indirect costs (the threat of covenant violation and its consequences) of credit lines. Overall, the existing empirical and theoretical literature on lines of credit has reached consensus that riskier firms should (and in practice do) shy away from bank-managed liquidity insurance but relies on rather general definitions of risk, whether they are market or accounting based.

There exist numerous channels through which a firm can be exposed to risk and that are likely to affect its financing decisions. Traditionally, the underlying risk of assets in place, the relative importance of intangible assets, and the risk of growth opportunities have been considered determinants of both capital structure (Jensen and Meckling, 1976, Myers, 1977, Harris and Raviv, 1990a) and cash holding choices (Kim, Mauer and Sherman, 1998, Opler *et al.*, 1999, or Almeida, Campello and Weisbach, 2004). Yet, risk is also likely to arise from the "current" part of a firm's balance sheet. In particular, current assets and liabilities reflect the structure of a firm's operating cycle, including the liquidity need it generates. To finance its day-to-day operations, a firm can then rely on cash or on alternative financing tools, such as factoring and accounts receivable securitization.[7] These last two solutions allow firms to capitalize on their (credit-worthy) accounts receivable. The cost of these financing sources is mechanically subject to the quality and riskiness of borrowing firms' customers. Provided that lines of credit are used to finance receivables, as documented in Petersen and Rajan (1997), their overall cost should also be impacted by customer risk and quality. In other words, supplier-customer relationships are likely to be a source of risk exposure for supplier firms and should thus affect their choice between cash and bank lines of credit as sources of liquidity.

Drawing on these results, I further investigate how customer risk might affect a firm's choice between cash and lines of credit as sources of liquidity. One of the major determinants of customer quality is the ability of a customer firm to honor its debts on time, if at all. As riskier or distressed customers are more likely to not honor their debts, supplier firms face a higher operating risk through the potential loss of future cash flows. This is all the more true for firms with sales that depend on one or several major customers. For example, Hertzel *et al.* (2008) and Kolay *et al.* (2015) observe negative abnormal returns for supplier firms following the extreme event of a major customer filing for bankruptcy. As such, firms facing greater uncertainty on the customer side of their activity should be more likely to miss debt repayment deadlines or to violate credit line (or, more broadly,

[7] See Klapper (2005) and Ketkar and Ratha (2001) for detailed presentations of the factoring and receivables securitization mechanisms, respectively.

debt) covenants. In addition, Demiroglu and James (2010) and Flannery and Wang (2011) show that the terms of credit line agreements are often subject to the quality (typically, the age) of a firm's accounts receivable.[8] Thus, banks are most likely to tighten the conditions under which they grant lines of credit to firms operating with riskier customers through higher spreads, lower maturities or more restrictive covenants.

Building on these rationales, my main testable hypothesis is as follows:

**Hypothesis 1** *Ceteris paribus, firms facing higher customer risk rely less on lines of credit as a source of liquidity (as opposed to relying on cash).*

Similarly, the marginal cost (e.g. the overall spread, or the tightness of covenants and the associated threat of violation) of opening and holding a line of credit is thus more likely to outweigh the related benefits (e.g. financial flexibility) for supplier firms facing high customer risk. As such, the previous hypothesis can be restated as follows:

**Hypothesis 1 bis** *Ceteris paribus, the cost of a line of credit is higher for firms facing higher customer risk.*

# 3 Data

## 3.1 Sample Selection

I draw my main sample (hereafter, the *Line of Credit Sample* or *LC sample*) from the LPC-Dealscan database. LPC collects information on loans to large U.S. corporations, primarily through SEC filings (e.g., 8-K and 10-K filings), reports from loan originators and the financial press. The LPC-Dealscan database thus contains detailed information on commercial loans made to U.S. firms, with data from the mid-1980s to 2013, which allows me to construct a large sample of credit line initiations. As reported in Acharya, Almeida and Campello (2013), the data are based primarily on syndicated loans and might thus be biased toward larger deals and, consequently, larger firms. Nevertheless, Carey and Hrycray (1999) report that the loans captured by the DealScan database account for 50% to 75% of the total value of commercial loans issued in the U.S. until 1992 and a greater fraction from 1995 onward[9].

The *LC sample* is constructed starting from a sample of corporate loans reported in LPC-Dealscan during the period 1987-2013 for which the borrowing firm can be matched

[8] Anecdotal evidence linking the access to revolving credit facilities and a supplier's receivables can be found in "Bankruptcy Fears Grip Auto-Parts Suppliers", published in the *Wall Street Journal* on January 26$^{th}$ 2009.

[9] Although no recent study assesses the actual coverage of commercial loans in the LPC-Dealscan database, one can assume that the trend reported in Carey and Hrycay (1999) has at least been constant through the present.

to a Compustat firm identifier.[10] I drop utilities, quasi-public and financial firms (i.e., firms with SIC codes greater than 5999 and lower than 7000, greater than 4899 and lower than 5000 and greater than 8999). I consider only long-term and short-term lines of credit, which are defined as loans with the the LPC field *"loantype"* equal to "364-day Facility", "Revolver/Line < 1 Yr", "Revolver/Line > = 1 Yr", or "Revolver/Line". I drop facilities that appear to be repeated (same borrowing firm and LPC loan identifier).[11] As loans are reported at the deal level, a given firm can have more than one line of credit initiation in the same quarter. In these cases, I sum the individual facility amounts for each firm-quarter observation and average the other variables (maturity, spread, fees, etc.) using the individual facility amounts as weights.

Then, following the methodology described in Section 3.2.1, I compute the yearly total amount of credit available through line(s) of credit for every sample firm. For each firm, I exclude every observation prior to the first reported line of credit initiation and after the last non-zero amount of available credit. This sample is then matched to Compustat annual data, as described in Section 3.2.3. In total, the *LC sample* is composed of 8,222 unique firms, representing a total of 67,145 firm-year observations over the 1987-2013 period.

Next, I match each *LC sample* supplier firm to its customers. The regulatory environment in the United States allows me to construct a sample of customer firms (hereafter, the *Customer Sample*) . In accordance with the Statement of Financial Accounting Standards (SFAS) No. 14 and 131, U.S. public firms are required to disclose the identity of any customer that accounts for at least 10% of their revenues, although some firms choose to report customers that account for less than 10% of their revenues. These data are reported in firms' annual 10-K filings and are available in the Compustat Customer Segment File. The database, however, only contains the name of the main customers reported by U.S. public firms.

The most efficient procedure used in the literature to identify the customer firms reported in the Compustat Customer Segment File is described in Fee and Thomas (2004) and Kale and Shahrur (2007). The first step consists in using a fuzzy-matching algorithm that compares the reported customer names (either complete or abbreviated) to the company names listed on CRSP (historical name structure) or Compustat.[12] In total, the *Customer sample* is composed of 2,520 unique customer firms for 3,564 unique supplier firms within the *LC sample*. The details of the main variables included in this sample are reported in Section 3.2.2.

[10] To do so, I rely on the file provided by Michael Roberts and used in Chava and Roberts (2008).

[11] I do not make any distinction between secured and unsecured loans. Given all of these restrictions, the average new line of credit is as follows: it amounts to $315 million, has a maturity of approximately 14 quarters, an average spread on drawn amounts of 1.89% and a commitment fee of 33bps.

[12] Further details regarding this procedure can be found on pp. 436-437 of Fee and Thomas (2004)

Table 1 presents the distribution of *LC sample* (supplier) firms across industries. As reported in column (1), manufacturing firms (4-digit SIC codes between 2000 and 3999) account for almost half of the overall firm-year observations (49.35%), while the second-most represented industry, i.e., the service industry (including firms with a 4-digit SIC code between 7000 and 8999), only represents 19.86% of the total sample. Regardless of the industry, the proportion of firms in each industry that report at least one identifiable major customer is relatively low and only reaches a maximum of 26.4% for the manufacturing industry. This observation first stems from the restrictions I impose on customer firms, which have to be included in the Compustat database. This implies that firms reporting only private firms as their major customers do not appear in the *Customer sample* as having identifiable main customers. In addition, as I chose to follow a conservative approach in identifying customer firms to limit Type I errors[13], I mechanically reduce the subsample of firms that appear to report at least one main client. Finally, firms might deliberately choose not to report identifiable customer names. In particular, Ellis, Fee and Thomas (2012) find evidence of potential strategic behavior by firms that choose not to disclose information about their customers that meet the minimum requirements of the U.S. Securities and Exchange Commission regulations.

Column (8) of Table 1 reports the industry mean relative size of main customers compared to their suppliers. I measure a customer firm's relative size as the ratio between the book value of its total assets and the total value of its suppliers' total assets. Depending on the supplier industry, customer firms appear to be on average 23.412 to approximately 78 times larger than their suppliers. In other words, the supplier firms in my sample are on average much smaller than their major customers. This suggests that my final sample is likely composed of relatively small intermediate goods producers or subcontractors. This is all the more true given that half of my sample is composed of manufacturers. A typical example would be that of Cherry Corp., which mainly sold sensors and other electronic components to the automobile industry during the sample period and had Ford and General Motors as major clients.

### 3.2 Main Variables

My tests combine data that come from multiple sources. It is thus useful to explain in detail how I construct the main variables used in this article.

[13]A Type I error, or false positive, occurs when I wrongfully identify a firm as a major client of a given supplier firm.

### 3.2.1 Line of credit data

I measure the reliance on lines of credit following Acharya, Almeida and Campello (2013). For each firm-quarter observation, I measure line of credit availability by summing all existing credit lines that have not yet matured. To do so, I assume that all credit facilities remain open until they mature. Thus, credit line availability for each firm-quarter (i,q) is defined as follows:

$$Quarterly\ LC_{i,q} = \sum_{t \leq q} LC_{i,t} \mathbb{1}_{\{Maturity_{i,t} \geq q-t\}} \tag{1}$$

where $LC_{i,t}$ is the total value of lines of credit initiated by firm $i$ in quarter $t$, $Maturity_{i,t}$ is the maturity of credit lines initiated by firm $i$ in quarter $t$, and $\mathbb{1}_{\{.\}}$ is the indicator function. I convert this firm-quarter measure into a firm-year measure of credit line availability by computing the yearly average *Quarterly LC* for each firm. This firm-year measure is denoted $Total\ LC$. The fraction of corporate liquidity that is provided by revolving credit facilities for firm $i$ in year t is then computed as:

$$LC\text{-}to\text{-}Cash_{i,t} = \frac{Total\ LC_{i,t}}{Total\ LC_{i,t} + Cash_{i,t}} \tag{2}$$

In addition, I construct a proxy for the financial cost of a firm's lines of credit. The cost of credit lines can be divided into two distinct but related sources. The first cost measure is the all-in drawn spread, which is defined as the annual spread (expressed as a percentage) over LIBOR paid for drawing down funds from an existing line of credit. The second measure of the cost of lines of credit are the annual fees (also expressed as a percentage) paid on undrawn amounts, typically called amortization fees or commitment fees. For each firm, I compute the yearly weighted average all-in drawn spread and the yearly weighted average commitment fee paid on available lines of credit, using individual facility amounts as weights. Following previous studies (see Booth and Booth ,2006, Carey and Nini, 2007, or Flannery and Wang, 2011), I aggregate these two costs to construct an overall measure of the yearly average cost of lines of credit, which will be referred to as *LC Cost* hereafter. I also construct the *LC Maturity* variables as the maturity in quarters of the available lines of credit for each sample firm in a year. If more than one line of credit is available for a given firm during a given year, *LC Maturity* is computed as the weighted average of the maturities of the available lines of credit, using individual facility amounts as weights. Similarly, I define the *Number of Covenants* variable as the number of covenants included in credit line agreements. The *LPC Dealscan* database identifies up to twenty-one specific covenant types that are included in debt contracts and regroups them into two main groups, namely financial covenants and net worth covenants. Financial covenants include, for example, capital expenditures, debt to EBITDA, EBITDA, interest coverage or leverage covenants. Net worth covenants include either net worth or tangible net worth provisions. I aggregate the number of distinct covenants included in each credit line agreement and define the number of covenants for each sample firm in each year as the yearly average number of covenants attached to all lines of credit opened in a given year.

Table 2 Panel A presents the descriptive statistics for all line of credit variables. *LC-to-Cash* is computed for all sample firms, while the cost (*Cost of LCs*), maturity (*LC Maturity*) and covenants (*Number of Covenants*) variables are only computed for firms exhibiting a non-zero amount of available lines of credit during a given year.

### 3.2.2 Customer Risk Data

To proxy for customer risk, I use three measures of default probability that capture the likelihood that a major customer will default or declare bankruptcy during a given year. My first measure is computed, in the spirit of Hillegeist *et al.* (2004), as the weighted average expected default probability of a supplier firm's major customers, based on the KMV-Merton[14] structural model, where the weights are the percentages of the supplier firm's sales to each major customer. This variable is denoted *Customer Risk - Merton* hereafter. My second measure is based on Campbell, Hilsher and Szilayi's (2008)(hereafter CHS) probability of default that uses both accounting ratios and market-related variables to assess the likelihood of corporate bankruptcy through a hazard model. Similarly, the overall risk measure is the weighted average probability of default of a given supplier's major customers and is referred to as *Customer Risk - CHS*.

My last measure is derived from a principal component analysis (hereafter PCA) and uses the first principal component from Altman's (1968) modified weighted average Z-score of a supplier firm's major customers[15], KMV-Merton's based customer risk measure and CHS-based customer risk measure (see Kim *et al.*, 2011, and Dhaliwal *et al.*, 2015, for similar approaches). This customer risk measure is denoted *Customer Risk - PC*. Appendix A and Appendix B contain the detailed computation process of my first two customer risk proxies, respectively.

Table 2 Panel B reports the summary statistics for the customer risk variables based on the Merton (1974) structural model and the CHS empirical hazard model.

[14] The model was originally designed and presented in Merton (1974)

[15] At the individual firm level, Altman's (1968) Z-score is computed as 1.2(WCR/Total Assets) + 1.4(Retained Earnings/Total Assets) + 3.3(EBIT/Total Assets)+0.6(Market Value of Equity/Total Liabilities) + 0.999(Sales/Total Assets) for manufacturing firms, and as 6.56(WCR/Total Assets) + 3.26(Retained Earnings/Total Assets) + 6.72(EBIT/Total Assets)+1.05(Market Value of Equity/Total Liabilities) for non-manufacturing firms.

### 3.2.3 Control variables

I follow Sufi (2009) in the definition of the main Compustat-based control variables that I use in the line of credit tests. I thus rely on a measure of book assets that is net of cash holdings, i.e., firm *Assets* are defined as *at - che*. The other Compustat-based variables are defined as follows (in terms of Compustat annual variable names). *Cash* is measured using *che*. Asset *Tangibility* is computed as *ppent* scaled by *Assets*. Firm *Size* is defined as the natural logarithm of *Assets*. Following Acharya, Almeida and Campello (2013), Tobin's Q is defined as the cash-adjusted market-to-book ratio and is given by *(Assets + prcc_fc ∗ sho - ceq)/Assets*. *Net Worth* is defined as *(ceq - che) / Assets*. *ROA* is the return on assets and is proxied by the EBITDA scaled by non-cash total assets, i.e., *oibdp/Assets*. *Industry Sales Volatility* is the 3-digit SIC industry median value of the within-year standard deviation of quarterly changes in firm sales scaled by the industry average asset value during the same year. Cash flow volatility (*CF Variability*) is based on the measure used in Mackie-Mason (1990) and is computed as the firm-level standard deviation of the annual change in the level of EBITDA, calculated over a lagged four-year period and scaled by average assets in the lagged period. I use two measures of information asymmetry. Firm *Age* is measured as the difference between the current year and the first year in which a firm appeared in Compustat. *S&P* is a dummy variable that is equal to one if a firm is included in one of the main S&P indices, i.e., the S&P 500, the S&P Midcap 400, and the S&P Smallcap 600. I also use two variables related to a supplier's trade credit. *Receivables* is measured as the ratio of a firm's total receivables to its total revenues and is computed as *rect/sale*. *Doubtful* is defined as the estimated proportion of annual sales accounted for by doubtful receivables and is given by *recd/sale*. All Compustat variables are winsorized at the $5^{\text{th}}$ and $95^{\text{th}}$ percentiles.

Following Acharya, Almeida and Campello (2013), I measure *LC sample* firms' exposure to systematic risk using asset unlevered beta. To do so, I unlever equity betas using the KMV-Merton model. Firm value is thus computed following the process described in Section 3.2.2. Asset betas are computed using the following formula:

$$\beta_{\text{KMV}} = \beta_{\text{Equity}} \frac{E}{V} N(d_1) \tag{3}$$

where $\beta_{\text{Equity}}$ is the equity beta computed using the past twelve monthly stock returns (extracted from CRSP) for each *LC sample* firm. In addition, I measure asset volatility using the numerical results yielded by the KMV-Merton model and denote it $\sigma_{\text{KMV}}$. As Acharya, Almeida and Campello (2013) find evidence that $\sigma_{\text{KMV}}$ is a better measure of total risk than $CF\ Variability$, I use it as a control variable in some regression specifications.

The descriptive statistics of all the aforementioned control variables are reported in Table 2 Panel C.

# 4 Empirical Results

## 4.1 Customer Risk and The Choice Between Cash and Lines of Credit

### 4.1.1 Univariate Results

Table 3 reports the univariate comparisons of the main line of credit variables (as described in Section 3.2.1) between a sample of firms with low customer risk and a sample of firms with high customer risk. Firms with low customer risk are identified as those ranked in the bottom quartile of the relevant customer risk measure, while firms with high customer risk are those ranked in the top quartile of the relevant customer risk measure.

Panel A of Table 3 presents the univariate comparisons of the LC-to-Cash variable. The bottom and top quartiles of each customer risk variable are drawn from the entire *LC Sample*. Firms in the bottom quartile of the Merton- (CHS-) based customer risk variable exhibit a mean ratio of available lines of credit to total liquidity of 54.9%(54.3%), which is significantly different at the 1% level from the 48.6% (48.8%) mean ratio observed for firms with high customer risk. These results remain robust to the exclusion of firm-years for which the amount of available lines of credit is equal to zero, as reported in Table 3 Panel B. In addition, the results remain unchanged when customer risk is proxied by the PCA-based measure.

Firms facing high customer risk also appear to bear the highest costs of bank liquidity. As shown in Table 3 Panel C, firms with low customer risk pay an average spread that is 33.8 bps to 48 bps lower than their high customer risk counterparts. In addition, Panel D suggests that firms facing the highest levels of customer risk tend to have more covenants attached to credit line agreements, relative to their counterparts that face lower customer risk levels. However, these differences appear to be small and even insignificant, depending on the customer risk proxy employed. Finally, Panel E shows that supplier firms with high customer risk tend to obtain shorter maturities for their new credit lines. The average maturity declines significantly, from nearly 15 quarters (i.e., nearly 4 years) for firms facing low Merton-based customer risk to barely 11.5 quarters (i.e., less than 3 years) for high Merton-based customer risk firms. The average difference in maturities is much smaller when relying on the other customer risk measures and is only significant at the 10% level when measuring customer risk using a CHS-based proxy.

Overall, these preliminary results suggest that, on average, firms facing higher customer risk rely less on lines of credit as a source of liquidity and are only able to obtain bank liquidity under less favorable terms. However, univariate results alone are not enough to conclude either that customer risk *does* increase the cost of bank liquidity or that it leads firms to rely more heavily on cash. The remainder of Section 4 thus focuses on various multivariate tests designed to test the hypotheses proposed in this paper.

#### 4.1.2 Firm-level regressions

My benchmark regression model includes all previously identified determinants of the choice between cash and lines of credit, as well as my customer risk measures. Each customer risk proxy is included separately. Overall, the regression equation is as follows:

$$\begin{aligned} LC\text{-}to\text{-}Cash_{i,t} &= \alpha + \beta_1 Customer\ Risk_{i,t} + \beta_2 Beta\ KMV_{i,t} \\ &+ \beta_3 ROA_{i,t\text{-}1} + \beta_4 Tangibility_{i,t\text{-}1} + \beta_5 Size_{i,t\text{-}1} \\ &+ \beta_6 Net\ Worth_{i,t\text{-}1} + \beta_7 Q_{i,t\text{-}1} + \beta_8 Ind.\ Sales\ Vol_{i,t} \\ &+ \beta_9 CF\ Variability_{i,t} + \beta_{10} SP\ dummy_{i,t} \\ &+ \beta_{11} Firm\ Age_{i,t} + \lambda_t + \gamma_i + \epsilon_{i,t} \end{aligned} \tag{4}$$

where $\lambda_t$ and $\gamma_i$ represent year and industry fixed-effects, respectively. Industry fixed effects are coded at the 2-digit SIC level. Because clustering effects could bias the statistical significance of the results owing to time series dependence, I adjust the standard errors in all regressions for clustering by firm.

Table 4 reports the results of the preliminary regressions. Regardless of the specification, I find that profitable, large, mature and low net worth firms with stable cash flows are more likely to rely on bank lines of credit as a source of liquidity. In Columns (1) to (3), I alternatively introduce the three customer risk variables presented in Section 3.2.2. The results consistently exhibit a negative and significant correlation between customer risk and the relative reliance on credit lines. The magnitude of the coefficient associated with the Merton-based measure of customer risk (-0.560) implies that a one-standard-deviation increase in customer risk (approximately 2.9%) decreases, on average, a firm's reliance on bank lines of credit by 1.624%, *ceteris paribus*. The effect of a one-standard-deviation increase is relatively similar when using alternate definitions of customer risk: -1.44% for the CHS-based measure and -2.14% for the PCA-based variable[16]. Although the economic significance of these results might seem relatively small, this result suggests that even minor (in magnitude) changes in customer risk affect a firm's choice between cash and bank credit lines. This is all the more true for extreme changes in risk faced by supplier firms from the customer side of their activity, i.e., when a firm's main customers are close to financial distress.

As customer risk proxies are most likely correlated with a firm's asset beta, my initial results could simply capture the correlation between corporate cash management choices

[16] The unreported standard deviation of the *Customer Risk - First PC* variable is approximately 1.02.

and systematic risk exposure. I thus control for the (unlevered) beta of a supplier firm's assets (*Beta KMV*) and report the regression results in columns (1) to (3) of Table 5. Regardless of the specification, the coefficient associated with *Beta KMV* appears to be significantly negative at the 1% level. This is consistent with the assumption that firms with high exposure to systematic risk rely more intensively on cash to meet their liquidity needs. As in Table 4, the evidence tends to suggest that customer risk is negatively correlated with the reliance on bank credit lines. The inclusion of systematic risk exposure only marginally affects both the magnitude and significance of customer risk estimates, which remain significantly negative at the 1% level. Furthermore, the economic significance of my results remains qualitatively unchanged, as a one-standard-deviation increase in customer risk is associated with a 1.48% (for the Merton-based measure) to 2.44% (for the PCA-based measure) decrease in the *LC-to-Cash* ratio. For the sake of completeness, I also control for asset volatility by including the *Var KMV* variable. The corresponding regression estimates are reported in Columns (4) to (6) and show that controlling for asset volatility does not affect my results. Altogether, these results suggest that the effect of customer risk on the choice between cash and lines of credit does not solely reflect the impact of systematic risk exposure on a firm's financing decisions.

In addition, being able to collect receivables is closely related to customer quality and, consequently, to customer risk. As such, I next investigate the effect of trade credit on the choice between cash and lines of credit and the extent to which it could affect my results regarding customer risk. Customers are usually deemed "bad" when they fail to honor their debts within the period contractually established with their supplier. Thus, transacting with such customers mechanically increases the share of a supplier's sales accounted for by pending invoices and potentially decreases the overall quality of its receivables. As access to bank lines of credit is often dependent on the quality of a firm's receivables, firms for which receivables represent a high share of their annual sales should thus exhibit lower *LC-to-Cash* ratios. This is all the more the case for true supplier firms that rely on a limited number of customers to generate a significant portion of their sales. Therefore, part of my results are likely to stem solely from the lower ability of firms with high customer risk to convert receivables into revenues, should my customer risk measures fail to capture other dimensions of risk.

To address this issue, I extend the regression model described in Equation 4 and control for the lagged receivables-to-sales ratio, which is defined as the total year-end total receivables scaled by the amount of total sales. I also control for the lagged estimated doubtful-to-sales ratio, which measures, albeit imperfectly, the share of pending invoices that are most likely not to be recovered. The corresponding regression estimates are reported in Table 6. These results exhibit an insignificant correlation between estimated doubtful receivables and the choice between cash and lines of credit. Conversely, they suggest that firms with high receivables-to-sales ratios rely more heavily on cash as a source of liquidity. This is consistent with the assumption that the ability to convert pending invoices into actual sales is positively correlated with the reliance on bank lines of credit. The evidence in Table 6 further shows that the negative effect of customer risk on the choice between cash and revolving credit facilities is robust to controlling for accounts receivable and doubtful accounts.

#### 4.1.3 Instrumental Variables Regressions

Although my results have thus far been robust, endogeneity is still likely to arise from unobserved omitted variables. In particular, I am unable to observe either part or all of the nexus of implicit contracts likely to exist between a firm and its customers (see Coase, 1937, Zingales, 2000, or Kale, Menaghetti and Shahrur, 2012). Provided that these factors are both more prevalent among major customers and correlated with a supplier's choice between cash and bank lines of credit, my previous findings might thus be biased. However, most concerning is the fact that I am also unable to observe determinants of bank credit supply that are also correlated with a firm's customer risk. Banks are indeed likely to redirect part or all of their credit supply toward firms with safer receivables for internal strategic reasons that are only partially, if at all, observable (e.g., following a change in risk management policy during a recession). I am, for example, unable to measure the extent to which lending banks are exposed to capital flow reversals. The banks that are the most sensitive to funding shocks (e.g., international commercial banks) are most likely to reduce credit availability and increase the cost of funds during economic downturns (see Puri *et al.*, 2011). In addition, there now exists a significant body of evidence showing that bank credit shortages have a negative impact on the economy, in particular on borrowing firms' output (see Jiménez *et al.*, 2012, or Paravisini *et al.*, 2014). Thus, not being able to observe banks' exposure to funding shocks might lead me to omit factors that are likely to simultaneously induce banks to ration available credit and impair the performance of a supplier firm's major customers. To address this issue, I use an instrumental variable approach.

I consider two main instruments. First, I rely on the lagged average idiosyncratic risk (volatility) of a supplier firm's main customers. Following Ang *et al.* (2009), idiosyncratic risk at the customer firm-year level is initially defined as the yearly standard deviation of regression residuals of the daily Fama and French (1992,1993) three-factor model. I also account for the correlation between customers' and suppliers' stock returns, even after controlling for systematic risk factors (Cohen and Frazzini, 2008). For each buyer-supplier pair, I thus compute idiosyncratic customer risk from the regression residuals of a customer's stock returns on Fama and French's three risk factors and its supplier's stock returns. Daily stock returns are extracted from the CRSP database. The daily Fama-French factors are obtained from Kenneth R. French's website. For each year, a supplier's idiosyncratic customer risk is then defined as the one-year-lagged weighted average idiosyncratic volatility of all identifiable major customers, using the contemporaneous percentages of the supplier firm's sales to each main customer as weights. In addition, I instrument my customer risk measures using a measure of credit line availability at the customer level. In particular, for each year, I construct an indicator variable that is equal to one if an individual customer has access to a line of credit and zero otherwise. At the supplier level, customer credit line availability is computed as the one-year-lagged weighted average of the aforementioned dummy variable.

Idiosyncratic customer volatility should be a valid instrument for two reasons. First, as it is specific to each customer firm, it is highly likely to be correlated with the probability of default at the individual supplier level. As such, my aggregated measure of idiosyncratic customer risk at the supplier firm level should also be correlated with each measure of customer risk. Furthermore, to the extent that idiosyncratic risk is diversifiable, it is unlikely to be directly reflected in a supplier firm's risk and thus in its choice between cash and lines of credit. In addition, due to its inherent nature, aggregate idiosyncratic customer volatility is unlikely to be correlated with banks' credit line supply to supplier firms. To some extent, banks are unlikely to acquire specific information about the customers (even major ones) of a potential client. Similar arguments apply when assessing the *ex ante* validity of credit line availability at the customer level as an instrument. In particular, not having access to a line of credit can be viewed as a characteristic of financially constrained firms (see Sufi, 2009). Customer credit line availability is thus likely to be correlated with a supplier firm's customer risk. However, it is very unlikely that customer firms' (lack of) access to a credit line is directly correlated with neither bank credit supply to supplier firms nor financing decisions at the supplier level.

The use of lagged variables should further alleviate concerns that my instruments are correlated with financing choices made at the individual supplier level. However, these lagged variables should still be correlated with the contemporaneous expected average probability of default of a firm's main customers, i.e., customer risk. Finally, to strengthen the *ex ante* validity of my instruments, I restrict my sample to supplier firms that do not share the same lead bank on any of their outstanding loans, with any of their customers, during a given year. To do so, I rely on the Dealscan database to identify all loans opened by Compustat firms, as well as the lead bank for each loan. I assume that loans remain open until they mature and that a lead bank does not change over the term of a loan. Although this leads to a much smaller sample size, relying on this restricted sample should ensure that my results are not due to banks using specific information about customer firms to determine the supply of credit lines that they are willing to direct to supplier firms.

Table 7 reports the results of the first-stage (Columns (1), (3) and (5)) and second-stage (Columns (2), (4) and (6)) regressions for each customer risk measure. To assess the *ex post* validity of my instruments, I report various test statistics. I first consider the first-stage exclusion F-test for my instruments, which are reported in Columns (1),(3) and (5). For two out of three customer risk proxies, the high F-stats (which are associated with p-values just above 1%) confirm the explanatory power of my instruments. In addition, the first-stage regression results mostly suggest that idiosyncratic customer risk and customer credit line availability are correlated with an individual supplier firm's customer risk. However, all F-stats are below the heuristic threshold of 10, thus revealing a potential weak instrument issue. To alleviate this concern, I report the Anderson-Rubin weak IV robust test for each specification in Columns (2), (4) and (6).[17] Under the null hypothesis, IVs are jointly equal to zero in the reduced-form model and overidentification restrictions are valid. Most important, this test is robust to the presence of weak instruments. Here, I am never able to reject the null hypothesis, which suggests that my instruments are indeed valid. I also control for whether my instrumental variables meet the under-identification restriction. To do so, I report the Kleibergen-Paap rank LM statistic for each second-stage regression in Columns (2), (4) and (6). The high test statistics suggest that I can reject the null hypothesis that my equations are under-identified, regardless of the customer risk measure employed and thus that my instruments are relevant. Finally, I focus on the Hansen J-test statistic and report the associated p-values in Columns (2), (4) and (6). All p-values are above the 10% threshold; thus, regardless of the customer risk proxy used, I do not reject the null hypothesis that my instruments are uncorrelated with with the error-term in the second-stage regression and that my model is well specified. This implies that my instrumental variables are exogenous to a supplier's choice between cash and lines of credit. The second-stage results reported in Columns (2), (4) and (6) exhibit a negative correlation between customer risk and the choice between cash and bank lines of credit. Overall, to the extent that my instruments are valid, the results in Table 7 suggest that greater customer risk leads supplier firms to rely less on lines of credit relative to cash.

Overall, the evidence here highlights how the conditions under which a firm operates on the product market are a key driver of its liquidity management decisions. Specifically, supplier firms facing high customer risk appear to rely less on bank-managed liquidity insurance. This effect furthermore appears to be economically significant compared to previously documented determinants of the reliance on credit lines.

## 4.2 Customer Risk and The Cost of Lines of Credit

The empirical evidence in Section 4.1 is based on the underlying rationale that firms facing higher risk on the customer side of their activity face a higher cost of bank credit

[17]Another solution would be to compare the first-stage F-stats to the Stock and Yogo critical values (see Stock and Yogo (2005). However, these critical values are only computed for i.i.d standard errors, which I do not assume here. As such, I choose to solely focus on the Anderson-Rubin weak IV test to assess the validity of my instruments, given a potential weak IV issue.

lines. To validate this assumption, this section focuses on the correlation between customer risk and various dimensions of the cost of bank liquidity for supplier firms.

### 4.2.1 Monetary Cost of Lines of Credit

I first focus on the monetary cost of lines of credit, which is proxied by an aggregated cost measure (*LC Cost*). I take the natural logarithm of this measure to allow for a non-linear relationship between the cost of bank credit lines and the set of chosen explanatory variables. The empirical model tested in this section then has the following form:

$$\begin{aligned} Log(LC\,Cost_{i,t}) \quad = \quad & \alpha + \beta_1 Customer\ Risk_{i,t} + \beta_2 New\ LC_{i,t} + \beta_3 LIBOR_{i,t} \\ & + \beta_4 Leverage_{i,t\text{-}1} + \beta_5 Beta\ KMV_{i,t} + \beta_6 ROA_{i,t\text{-}1} \\ & + \beta_7 Tangibility_{i,t\text{-}1} + \beta_8 Size_{i,t\text{-}1} + \beta_9 Net\ Worth_{i,t\text{-}1} \\ & + \beta_{10} Q_{i,t\text{-}1} + \beta_{11} Ind.\ Sales\ Vol_{i,t} \\ & + \beta_{12} CF\ Variability_{i,t} + \beta_{13} SP\ dummy_{i,t} + \beta_{14} Firm\ Age_{i,t} \\ & + \lambda_t + \gamma_i + \epsilon_{i,t} \end{aligned} \tag{5}$$

where *New LC* is the total amount of lines of credit raised during a given year scaled by total non-cash assets[18], *LIBOR* is the annualized weighted average level of the LIBOR in the quarter during which a line of credit was raised, and *Leverage* is past book leverage. All other controls variables are defined as in Equation 4. I control for firm and industry fixed effects by including year dummies ($\lambda_t$) and industry dummies ($\gamma_i$), where industries are identified at the 2-digit SIC level. Finally, standard errors are clustered by firm.

Table 8 reports results for the cost regression models. The coefficients on the customer risk proxies reported in Columns (1) to (3) suggest that the cost of lines of credit is on average greater for firms that operate with riskier customers, although statistical significance for the estimate on *Customer Risk - Merton* is weaker (with a p-value of 0.174). As these results could be driven by the chosen form for the cost of bank credit lines, I re-run the regression models described in Columns (1) to (3) of Table 8 using *LC Cost* as a dependent variable and report the corresponding results in Columns (4) to (6) of Table 8. The overall significance of the different customer risk estimates appears to be improved, although the p-value remains above the 10% threshold when relying on the Merton-based measure of customer risk (and is equal to 0.102). Altogether, these results suggest that the cost of obtaining new lines of credit is higher for supplier firms that face higher customer risk through higher spreads paid on either withdrawn or outstanding amounts.

[18] This measure differs from the *Total LC* variable. *New LC* only includes new lines of credit, while *Total LC* is computed using new lines of credit and existing lines of credit that have not yet matured.

### 4.2.2 Credit Line Covenants

I further investigate the correlation between customer risk and the terms of bank credit lines and first focus on the number of performance-based (or "financial") covenants included in credit line agreements. The *LPC Dealscan* database identifies up to twenty-one specific performance-based covenant types that are included in debt contracts. The yearly number of covenants for each sample firm is defined as the yearly average number of covenants attached to all lines of credit opened in a given year. My final measure of the number of covenants is then defined as the natural logarithm of the total number of covenants. I then regress this covenant intensity measure on the set of explanatory variables described in Equation 5.

Table 9 reports regression estimates for the financial covenants models. Panel A presents results for the baseline regression model. The coefficient on customer risk is insignificant in two out of three cases (Columns (1) and (3)) and is only significant when defining customer risk through the CHS hazard model (Column (2)). Although these results do not allow me to derive any consistent conclusion regarding the effect of customer risk on the number of covenants attached to credit line agreements, the customer risk estimate in Column (2) (and, to a lesser extent, Columns (1) and (3)) suggests that firms facing higher customer risk are on average subject to fewer covenants. In addition, the coefficient on *ROA* is consistently negative and significant at the 1% level. This implies that some weaker firms obtain credit line agreements that include a lower number of covenants.

Although they might seem counter-intuitive, these results may reflect the "relative importance of future cash flows versus collateral in repaying a line of credit" (see Flannery and Wang, 2011). In particular, financial covenants are less likely to be relevant for firms with low operating cash flows. To test this possibility, I sort firms based on whether their EBITDA is above or below the median of the overall yearly EBITDA distribution and report the results in Panel B of Table 9. Consistent with the aforementioned hypothesis, the coefficients on the customer risk proxies and ROA are only significant in the low EBITDA subsample.

More broadly, the latter hypothesis implies that banks are more prone to imposing non-performance-based covenants on firms with low operating performance and high customer risk. To test this implication, I rely on the LPC Dealscan database to collect information regarding non-financial covenants (these covenants include borrowing base provisions, dividend restrictions, asset sweeps, equity sweeps and debt sweeps). Definitions of non-financial covenants are reported in Appendix C. Table 10 Panel A reports detailed univariate comparisons of the yearly mean number of non-financial covenants attached to new credit line contracts between a sample of low customer risk and a sample of high customer risk *LC sample* firms. These two subsamples are defined following Section 4.1.1.

Nearly all of the results suggest that non-financial covenants are more often included in credit line contracts opened by supplier firms with high customer risk. Approximately 29.50% of credit lines opened by firms in the sample of firms in the top quartile of the Merton-based measure of customer risk include a borrowing base provision. This share declines to 16.50% when focusing on supplier firms in the bottom quartile of the distribution, and the difference is significant at the 1% level. In other words, lenders are more likely to tie the value of a line of credit to the value of pre-specified collateral when customer risk is high. Firms with high customer risk also appear to be more often subject to dividend restrictions in their credit line contracts. Table 10 Panel A further suggests that banks are more inclined to include sweep covenants in credit line agreements opened by riskier suppliers, although results are only significant for two out of three customer risk measures. This nonetheless highlights how lenders are most willing to ensure that cash flows are used to repay opened loans when dealing with high customer risk suppliers.[19]

Next, I repeat the analysis presented in Table 9 Panel B on non-financial covenants and report the regression estimates in Table 10 Panel B. The dependent variable is here defined as the natural logarithm of the total number of non-financial covenants (sweep covenants, dividend restrictions and borrowing base provisions) attached to credit line contracts opened during a given year. The coefficients on the customer risk proxies appear to be significantly positive only for low EBITDA firms, although this result holds for two out of three customer risk measures. This suggests that lending institutions are more likely to either ensure that cash flows are used to redeem outstanding debts or to tie the value of available funds to that of pre-specified collateral when dealing with risky supplier firms. In addition, the ROA estimate is consistently significant and negative only for the subsample of low EBITDA suppliers.

Overall, results thus far suggest that supplier firms with high customer risk are only able to open lines of credit at a higher cost. In particular, lending institutions charge higher overall spreads to riskier suppliers. Customer risk and covenants, however, do not appear to be equally relevant for all firms. Banks appear to impose more non-financial covenants only on suppliers with high customer risk and low operating cash flows. Consequently, financial covenants seem to be less relevant for such firms. These tighter conditions on access to lines of credit are likely to explain why high customer risk supplier firms appear to shy away from bank credit lines.

[19] In unreported tests, I repeat the same univariate comparisons on the covenant strictness measure defined by Murfin (2012) but find no significant difference between high and low customer risk suppliers.

# 5 Robustness Tests

## 5.1 Propensity Score Analysis

One potential endogeneity issue that might affect my model stems from the existence of omitted variables that are correlated with both customer risk and the choice between cash and bank lines of credit. In particular, the measures relied on to assess customer risk are likely to capture nonlinear effects if the controls used in the different regression models do not adequately account for differences between supplier firms facing low customer risk and those facing high customer risk. I thus use a propensity score matched sample to correct for any potential endogenous selection on observed variables (see Dehejia and Wahba, 2002).

Therefore, I first estimate the probability that a supplier firm faces low customer risk during a given year. The dependent variable is equal to one if a supplier firm is in the bottom quartile of the distribution for a given customer risk measure during a given year and is equal to zero if a firm is in the related top quartile. I use the set of control variables used the LC-to-Cash model described in Equation 4. I also include *Cash* and *Leverage* as control variables. This allows me to control for potential differences in both cash holdings and capital structure between suppliers facing low customer risk and suppliers facing high customer risk. Columns (1) , (3) and (5) of Table 11 Panel A report the marginal effects of these regressions. Next, I match each observation in the bottom quartile of each customer risk variable (i.e., with low customer risk) to a firm in the top quartile of the same customer risk variable (i.e., with high customer risk) with the closest propensity score. I match without replacement and require the propensity scores for each matched pair to be within $\pm 1\%$. Depending on the customer risk measure used, the resulting sample consists of from 947 (for the PCA based measure) to 1253 (for the CHS based measure) low customer risk supplier-years matched to from 947 to 1253 high customer risk supplier-years, respectively.

I perform several diagnostic tests to assess the validity of the matching procedure (see Fang *et al.*, 2014, or Dhaliwal *et al.*,2015). If the matching procedure is indeed successful, I should find that (i) the control variables used to create the matched sample do not explain any variation in whether matched supplier firms face low or high customer risk, (ii) the means of the matched control variables are not statistically different for suppliers with low and high customer risk, and (iii) the difference in propensity scores between low customer risk suppliers and high customer risk suppliers is on average insignificant and in the [-1%;1%] interval.

To test the first prediction, I run the regression model presented in Columns (1), (3) and (5) of Table 11 on the suitable matched sample and report the results in Columns (2), (4) and (6), respectively. The results show that none of the control variables remain statistically significant and thus do not explain any variation in whether a supplier faces low or high customer risk. Next, I examine the difference between the propensity scores and matched control variables of suppliers facing low customer risk and those facing high customer risk. The related univariate comparisons of the means are reported in Panel B of Table 11. The results show that the mean difference in propensity scores is not statistically significant and therefore trivial. In addition, the means of the matched control variables appear not to be statistically different across each pair of matched subsamples. Overall, these tests suggest that the matching procedure is valid and successful.

Panel C of Table 11 presents the results from my main LC-to-Cash regression model described in Equation 4. Consistent with previous findings, the results suggest that firms facing higher customer risk rely less on bank on lines of credit relative to cash, on average. In addition, using cash holdings as a control variable in the matching procedure ensures that, at least to some extent, the results cannot be attributed to high customer risk suppliers holding more cash than their low customer risk counterparts. Similarly, controlling for leverage when constructing the matched samples allows me to conclude that firms' reliance on lines of credit as a source of liquidity is, even to a limited extent, distinct.

To further assess the robustness of my initial regression results, I run the matching procedure on the subsample of firms for which I am able to measure the cost of opened lines of credit (i.e., to measure compute *LC Cost*). For each customer risk measure, each firm-year observation corresponding to a low customer risk supplier is matched with a firm-year observation associated to a "similar" high customer risk supplier. Firms are matched without replacement using the probit regression model described above, and I require the propensity scores for each matched pair to be within $\pm 1\%$. Depending on the customer risk measure used, the resulting sample consists of from 96 (for the Merton-based measure) to 270 (for the CHS based measure) low customer risk supplier-years matched to from 96 to 270 high customer risk supplier-years, respectively[20]. I then run the regression model described in Equation 5 on each matched sample and report the results in Panel D of Table 11. Despite the drastically reduced sample sizes, the results globally suggest that suppliers facing higher customer risk are able to obtain lines of credit at a higher cost than supplier firms operating with safer customers. The statistical significance is however weaker, especially for the Merton-based customer risk measure.

## 5.2 Major Customer Reporting

As described in Section 3.1, Financial Accounting Standards (SFAS) No. 14 and No. 131 of the Financial Accounting Standards Board (FASB) allow me to identify major cus-

[20]In unreported tests, I find that the matching procedure is successful, regardless of the customer risk proxy employed.

tomers for a subsample of Compustat - LPC Dealscan supplier firms (i.e., LC sample firms). SFAS No. 14 of the FASB requires that firms report information for segments including principal customers that account for at least 10% of their overall consolidated sales, for fiscal years ending after 1977. In addition, prior to 1997, supplier firms were also required to report all customers they considered important to their overall business operations. In other words, firms were allowed to disclose the identity of customer firms that accounted for less than 10% of their total revenues. In 1997, FASB revised the SFAS No. 14 through the issuance of SFAS No. 131, which rendered optional the disclosure of customers representing less than 10% of consolidated sales.

To alleviate potential endogeneity concerns due to strategic disclosure choices for customers that are below the 10% cutoff and to ensure consistency over time, I exclude from the sample firms that report customers that account for less than 10% of sales. I then run the *LC-to-Cash* and *LC Cost* regression models described in Equations 4 and 5, respectively. The results are reported in Table 12. Columns (1) to (3) present regression estimates for the LC-to-Cash empirical model. Excluding firms that report customers below the 10% threshold slightly changes the magnitude of the estimated correlation between customer risk and the choice between cash and bank lines of credit but does not impact its direction or overall significance (regardless of the definition of risk employed). In addition, Columns (4) to (6) suggest that the positive correlation between customer risk and the cost of bank lines of credit is globally robust to the use of a tighter definition of major customers. In unreported tests, I also test the covenant regression model on the restricted sample and find qualitatively similar results. Altogether, the evidence reported in this section suggests that my initial results were not driven by firms choosing to report customers accounting for less than 10% of their aggregated revenues.

### 5.3 Customer Risk and Customer Concentration

While the previous section alleviates part of the endogeneity concerns that my results might suffer from, it also highlights an important feature of my sample: customer risk is only computed for firms that report the existence (and identity) of major customers.

Winning the business of a major customer is a non-trivial event in the life of firm. Depending on a single large customer to generate a significant fraction of annual revenues allows a firm to enter into long-lasting trading relationships, which could, for example, foster innovation at the supplier firm level and increase product quality. Despite these potential benefits, some evidence in both the economic and the financial literature suggests that high customer concentration also induces costs for the supplier (see Lustgarten, 1975 or Williamson, 1979), which mainly stem from the advantageous bargaining position held by major customers. In this spirit, Klapper, Laeven, and Rajan (2012) find that large, financially stable firms borrow via trade credit from their smaller suppliers and obtain their most favorable trade credit terms from those same small suppliers. For example, Walmart's accounts payable accounted for nearly all of its short-term funding and approximately three-quarters of its total debt at the end of fiscal year 2009. Overall, the existing literature suggests that customer concentration can either reduce (Lustgarten, 1975) or increase (Patatoukas, 2012) profitability at the supplier level[21] but also increases risk and is, consequently, associated with higher costs of equity and debt (Dhaliwal *et al.*, 2015).

As such, the effect of customer risk on either the choice between cash and lines of credit or the cost of bank credit lines observed in this study could be artificially caused by (or biased by) the thus far unobserved potential underlying effect of customer concentration on liquidity management decisions at the supplier firm level. To alleviate this concern, I extend the regression models defined by Equation 4 and Equation 5 by explicitly controlling for a supplier firm's customer-base concentration. I measure annual customer concentration following Patatoukas (2012) and define it as the sum of the squared sales shares to each major customer during a given year. The regression estimates are reported in Table 13.

Columns (1) to (3) of Table 13 present the results for the *LC-to-Cash* regression model. The negative correlation between customer risk and the choice between cash and lines of credit remains significant at the 1% level across all three measures of customer risk. However, these results fail to exhibit any statistically significant effect of customer concentration on the reliance on credit lines as a source of liquidity. This suggests that the riskiness of major customers is indeed an important determinant of firms' cash management choices, beyond the fact that a supplier firm relies on a limited number of customer for a large portion of sales. In addition, Columns (4) to (6) report the regression estimates for the *LC Cost* empirical model. The evidence here suggests that higher customer risk is indeed associated with a higher cost of lines of credit. Moreover, my results exhibit a positive but weak correlation between the cost of bank credit lines and customer concentration. Altogether, the evidence reported in this section suggests that the effect of customer risk on cash management decisions cannot be attributed solely to the underlying impact of customer concentration.

## 5.4 Other Robustness Tests

I conduct several other robustness checks regarding firms' relative reliance on lines of credit as a source of liquidity: I include book leverage and capital expenditures in all the *LC-to-Cash* and *LC Cost* OLS regression models and find similar results. I also explicitly

[21] Irvine, Park and Yildizhan (2016) further investigate this issue and find that the negative effect of customer concentration on profitability is concentrated in the early years of the business relationship but becomes positive as the relationship matures.

account for the presence of crisis years (2007-2008) in my data. In particular, my results are robust to the exclusion of these years from the sample, as well as to the inclusion of crisis, post-crisis and pre-crisis dummy variables. I then control for customer-base concentration risk, asset volatility and trade credit components (accounts receivable, doubtful accounts and inventories) in the *LC-to-Cash* IV-2SLS analysis. Overall, my results remain qualitatively unchanged. I re-run the covenant analysis, sorting firms alternatively on size, profitability, net sales, or ordinary income and, in each case, find similar results. I further replace the unlevered beta of assets by the beta of equity in all regression models. This does not affect my results. Finally, I reproduce my analysis using varying monthly probabilities for the CHS-based measure of customer risk. In particular, I rely on the regression estimates reported by CHS for 1-month, 6-month and 12-month horizons. My results are again unchanged.

# 6 Concluding Remarks

This paper examines the impact of customer risk on cash management decisions at the supplier firm level. I use a matched buyer-supplier sample of U.S. industrial firms to examine whether dealing with potentially distressed customers affects a supplier's choice between cash and lines of credit. I find that firms facing high customer risk hold relatively more cash, even after controlling for previously documented risk factors. My results further suggest that customer risk increases the cost of lines of credit, either through higher spreads or a larger number of covenants. Overall, this study highlights one channel through which buyer-supplier relationships can shape corporate financial policies.

While this study is based on a sample of public U.S. firms with major customers, my results can be extended to a broader set of firms. First, the existing decline in the vertical integration of firms (see Dimitrov and Tice, 2006) and the growing trend of firms focusing on a limited number of key partners has led to a drastic increase in the prevalence of buyer-supplier relationships for most U.S. firms. Furthermore, the importance of customers in how suppliers can meet their liquidity needs has become a major focus for SMEs worldwide. As SMEs account for the vast majority of firms and a significant fraction of several major countries' gross domestic products (GDPs), their impact on the economy is non-trivial. As of March 2015, SMEs directly accounted for approximately 13.2% of U.S. GDP, 16.5% of French GDP, 13.7% of Chinese GDP and 13.7% of Brazilian GDP.[22] Understanding their operating environment and financing possibilities is thus a crucial issue. As such, although it contributes new insights into firms' financial decisions, this study allows for further detailed research on this topic.

[22] See "La face méconnue des entreprises de taille moyenne: une contribution vitale á l'économie", carried out by Oxford Economics for HSBC.

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# Appendix A Computing the KMV-Merton probability of default

Under the KMV-Model (see Merton, 1974), the total value of a firm is supposed to follow:

$$\frac{dV}{V} = \mu dt + \sigma_V dW \tag{6}$$

where V is the total value, $\mu$ is the expected continuously compounded return on $V$, $\sigma_V$ is the volatility of firm value and $W$ is a standard Wiener process. In addition, assume that the firm issued one discount bond maturing in $T$ periods. Under these assumptions, the equity of the firm is a call option on the underlying value of the firm, with a strike price equal to the face value of the firm's debt and a time-to-maturity $T$. Following the Black and Scholes (1973) pricing model, the value of the equity is then:

$$E = VN(d_1) - e^{-rT} FN(d_2) \tag{7}$$

where $E$ is the market value of a firm's equity, $F$ is the value of a firm's debt, $r$ is the instantaneous risk-free rate, $N(.)$ is the cumulative standard normal distribution function, $d_1$ and $d_2$ are given by:

$$d_1 = \frac{ln(V/F) + (r + \frac{1}{2}\sigma_V^2)T}{\sigma_V \sqrt{T}} \tag{8}$$

$$d_2 = d_1 - \sigma_V T \tag{9}$$

Given the value of equity, the underlying value of the firm's total assets is given by:

$$V = \frac{E + e^{-rT} FN(d_2)}{N(d_1)} \tag{10}$$

Since the market value of equity is a function of the total value of the firm and time, the volatility of the firm's equity can computed using using Ito's Lemma:

$$\sigma_E = \frac{V}{E}\frac{\partial E}{\partial V}\sigma_V = \frac{V}{E}\frac{1}{N(d_1)}\sigma_V \tag{11}$$

To implement the model, I need to numerically solve simultaneously equations (10) and (11). First, following Crosbie and Bohn (2001) and Vassalou and Wing (2004), I assume $T = 1$ and thus consider a 1-year horizon, and use short-term debt plus one half of long-term debt to proxy for the face value of debt $F$. Such a convention is a known rule of thumb that allows to fit the KMV-Merton model to a annual horizon, and that takes into account the fact that long-term debt may not mature until after the horizon of the default probability computation. Equity volatility is estimated as the historical yearly volatility of stock returns. I measure the risk-free rate $r$ as the Treasury-Bill rate, which is provided by the U.S. Department of the Treasury.

As starting values for firm value and asset volatility, I respectively use $V = F + E$ and $\sigma_V = \sigma_E(E/(F+E))$. I iterate on $V$ and $sigma_V$ until the procedures converges, i.e. until I obtain values of $V$ and $\sigma_V$ that are consistent with the observed values of $E$, $F$ and $\sigma_E$. I then compute the implied expected return on asset $\mu$. Using these numerical solutions, the firm's distance-to-default is given by:

$$DD = \frac{ln(V/F) + (\mu - \frac{1}{2}\sigma_V^2)T}{\sigma_V\sqrt{T}} \tag{12}$$

Finally, the corresponding probability of default is:

$$\pi_{\text{KMV,T=1}} = -N(DD) \tag{13}$$

As the KMV-Merton model only yields point estimates, I use the yearly cumulative probability of default to proxy for customer risk during a given year. To do so, I use the estimated $\mu$ and $\sigma_V$ to compute the implied probability of default for a 1-quarter, 2-quarter and 3-quarter horizon. The yearly cumulative probability of default for each client firm is then given by:

$$\pi_{\text{KMV}} = 1 - \prod_{t \in \mathbb{T}}(1 - \pi_{\text{KMV,T=t}}) \tag{14}$$

where $\mathbb{T} = \{0.25; 0.5; 0.75; 1\}$.

Finally, since firms might report several customers for a given year, I construct a weighted average of the client firms' probability of default as follows:

$$Customer\ Risk_{\text{KMV}} = \sum_{j=1}^{n} \pi_{\text{KMV,j}} \cdot Key\ Customer\ Percentage\ Sold_j \tag{15}$$

where $n$ is the number of client firms reported by a given supplier firm, $\pi_{\text{KMV,j}}$ is the probability of default of the $j^{th}$ customer, and $KeyCustomer\,PercentageSold_j$ is the percentage of the firm's sales to the $j^{th}$ customer.

# Appendix B Computing The CHS Probability of Default

Campbell, Hilsher and Szilagyi (2008) build a dynamic logit model to estimate the probability of bankruptcy of U.S. firms. More precisely, according to their model, the probability of bankruptcy at a 1-year horizon, using quarterly data, is computed as:

$$\pi_{\text{CHS,T=1 year}} = \frac{1}{1 + e^{\text{-CHSScore}}} \tag{16}$$

where:

$$\begin{aligned} CHSScore \;\; = \;\; & \text{- } 9.164 \text{ - } 20.264 \cdot NIMTAAVG + 1.416 \cdot TLTMTA \\ & \text{- } 7.129 \cdot EXRETAVG + 1.411 \cdot SIGMA \text{ - } 0.045 \cdot RELSIZE \\ & \text{- } 2.132 \cdot CASHMTA + 0.075 \cdot MB \text{ - } 0.058 \cdot PRICE \end{aligned} \tag{17}$$

CHS define $NIMTAAVG$ as the average quarterly net income to market value of total assets ratio in the past twelve months, $TLTMTA$ as total liabilities scaled by the market value of total assets, $EXRETAVG$ the yearly average quarterly excess return on a firm's equity compared to the S&P 500 in the past twelve months, $SIGMA$ as the quarterly volatility of stock returns, $RELSIZE$ as firm size (its market capitalization) relative to the S&P 500 entire market value, $CASHMTA$ as total cash to the market value of total assets, $MB$ as the market-to-book ratio, and $PRICE$ as a firm's stock price.

In order to measure customer risk in a given year, I compute the cumulative probability of default at a 1-year horizon. To do so, I assume that the probability of default for each client firm within each month in a given year does not vary with the horizon. Given the marginal probability of default, the yearly cumulative probability of bankruptcy is given by:

$$\pi_{\text{CHS}} = 1 \text{ - } (1 \text{ - } \pi_{\text{CHS,T=1 year}})^{12} = 1 \text{ - } \left( \frac{e^{\text{-CHSScore}}}{1 + e^{\text{-CHSScore}}} \right)^{12} \tag{18}$$

Similarly to Section A, yearly customer risk is then defined as follows:

$$Customer\ Risk_{\text{CHS}} = \sum_{j=1}^{n} \pi_{\text{CHS,j}} \cdot Key\ Customer\ Percentage\ Sold_j \tag{19}$$

## Appendix C Data Definition

This table presents variable definitions. Variables are computed for each firm and each year. * indicates that the variable is defined using Compustat data items.

| Name | Description |
|---|---|
| *Credit Lines Variables (Source(s): LPC Dealscan)* | |
| - LC-to-Cash | Proportion of yearly available liquidity accounted for by bank lines of credit. Includes all credit lines opened during a given year, as well as existing lines of credit that have not yet matured. For further details, see Acharya, Almedia and Campello (2013) |
| - LC Cost | Yearly weigthted average overall cost of newly opened lines of credit, using individual facility amounts as weights. At the individual facility level, it is defined as the sum of the fixed commitment cost and the spread over LIBOR paid on withdrawn amounts |
| - LC Maturity | Yearly weighted average maturity of *newly opened* lines of credit, using individual facility amounts as weights. |
| - New LC | Yearly total amount of *newly* opened credit lines scaled by non-cash total assets |
| - Number of (Fin.) Covenants | Yearly average number of both financial and net worth covenants attached to newly opened lines of credit. |
| *Non Financial Covenants Variables (Source(s): LPC Dealscan)* | |
| - Borrowing Base | This covenant ensures that the loan is backed by adequate collateral which can either be transferred to the lender in case of default or limit the amount of available funds. |
| - Dividend Restriction | This covenant limits the magnitude and type of corporate payouts in the form of dividends and repurchases. |
| - Asset Sweep | This covenant requires that a part of the proceeds from asset sales should first be used to pay down the loan. |
| - Debt Sweep | This covenant requires that a part of the proceeds from debt offerings should first be used to pay down the loan. |
| - Equity Sweep | This covenant requires that a part of the proceeds from equity offerings should first be used to pay down the loan. |
| *Customer Risk Variables (Source(s): COMPUSTAT, CRSP, LPC Dealscan)* | |

| Name | Description |
| --- | --- |
| - (Customer) Risk - Merton | Yearly weighted average expected default probability of a supplier firm's major customers, based on the KMV-Merton structural (see Merton, 1974) model, and where the weights are the percentages of the supplier firm's sales to each major customer |
| - (Customer) Risk - CHS | Yearly weighted average expected default probability of a supplier firm's major customers, based on Campbell, Hilsher and Szilagyi's (2008) hazard model, and where the weights are the percentages of the supplier firm's sales to each major customer. |
| - (Customer) Risk - PC | First principal component from Altman's (1968) modified weighted average Z-score of a supplier firm's major customers, KMV-Merton's based customer risk measure and CHS-based customer risk measure. |
| - Customer Idiosyncratic Risk | One year lagged weighted average idiosyncratic volatility of all identifiable major customers, using the contemporaneous percentages of the supplier firm's sales to each main customer as weights. Idiosyncratic volatility is computed, following Ang et al. (2009), as the standard deviation of regression residuals of the daily Fama and French (1992,1993) three-factor model. Also referred to as "Cust. Idio. Vol.". |
| - Customer LC dummy | One year lagged weighted average of majors customers who have access to a line of credit, using the percentages of the supplier firm's sales to each major customer as weights. Also referred to as "Cust. LC dummy". |
| *Supplier Firm Characteristics (Source(s): COMPUSTAT, CRSP)* | |
| - ROA | oibdp / (at - che) * |
| - Tangibility | ppent / (at - che) * |
| - Size | log(at - che) * |
| - Leverage | blev / (at - che) * |
| - Net Worth | (ceq - che) / (at - che) |
| - Q | [(at - che) + prcc_fc sho - ceq] / (at - che) * |
| - Receivables | rect / sale * |
| - Doubtful | recd / sale * |
| - Industry Sales Volatility | Three-digit SIC industry median value of the within-year standard deviation of quarterly changes in firm sales scaled by the industry average asset value during the same year. Also referred to as "Ind. Sales Vol.". |

| Name | Description |
| --- | --- |
| - CF Variability | Firm-level standard deviation of annual change in the level of EBITDA, calculated over a lagged four-year period and scaled by average assets in the lagged period. See Mackie-Mason (1990) for further details. |
| - S&P dummy | Dummy variable that is equal to one if a firm is included in one of the main S&P indices, i.e. the S&P 500, the S&P Midcap 400, and the S&P Smallcap 600. |
| - Firm Age | Difference between the current year and the first year in which a firm appeared in the COMPUSTAT. |
| - Beta KMV | Exposure to systematic risk, computed as the unlevered beta of assets. Equity betas are unlevered using the KMV-Merton model. See Merton (1974), Acharya et al. (2013) and Appendix A for further details. |
| - Var KMV | Asset volatility, as induced by the KMV-Merton model when computing the unlevered beta of a firm's assets. |

**Table 1. Distribution of Sample Firms Accross Industries**

The sample consists of up 8,222 unique industrial Compustat firms (utilities, quasi-public and financial firms are excluded) that are included in the LPC-Dealscan database from 1987 to 2013. This table presents various statistics at the industry level. Industry are identified at the 4-digit SIC code level: *Agriculture, minerals and construction* corresponds to SIC codes between 0000 and 1999, *Manufacturing* corresponds to SIC codes between 2000 and 3999, *Transportation and communications* corresponds to SIC codes between 4000 and 4899, *Trade - Wholesale* corresponds to SIC codes between 5000 and 5199, *Trade - retail* corresponds to SIC codes between 2500 and 5999, and *Services* corresponds to SIC codes between 7000 and 8999. Column (1) reports the proportion of the *LC sample* accounted for by each industry. Column (2) reports the industry average proportion of the *LC sample* corresponding to firms with non-zero available line of credit. Column (3) presents the the industry average proportion of the *LC sample* corresponding to firms that reported at least one major client. Column (4) reports the industry average *LC-to-Cash* ratio for firms with non-zero available line of credit. Column (5) reports the industry average proportion of firms that reported at least one major client within the subsample of firms that have a non-zero available line of credit. Column (6) presents the industry average proportion of firms with non-zero available line of credit within the subsample of firms that reported at least one major customer. Column (7) reports the industry average *LC-to-Cash* ratio for firms that reported at least one major customer. Column (8) reports the industry average relative size of disclosed major customers relative to their respective suppliers. Size is here defined as the total book value of assets.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Total LC Sample | | | LC $> 0$ | | # major clients $> 0$ | | |
| *Industry* | % of sample | Has LC | Reports Clients | LC/Cash | Reports Clients | Has LC | LC/Cash | Cust. Rel. Size |
| Agriculture, Minerals and Construction | 8.45% | 0.853 | 0.227 | 0.782 | 0.239 | 0.897 | 0.730 | 23.412 |
| Manufacturing | 49.35% | 0.761 | 0.264 | 0.723 | 0.255 | 0.735 | 0.514 | 60.021 |
| Transportation and Communication | 7.27% | 0.831 | 0.117 | 0.757 | 0.119 | 0.844 | 0.625 | 28.601 |
| Trade - Wholesale | 5.24% | 0.790 | 0.130 | 0.810 | 0.132 | 0.803 | 0.632 | 36.256 |
| Trade - Retail | 9.83% | 0.833 | 0.018 | 0.757 | 0.018 | 0.828 | 0.587 | 38.040 |
| Services | 19.86% | 0.733 | 0.139 | 0.652 | 0.130 | 0.687 | 0.398 | 78.838 |

## Table 2. Summary Statistics

This table reports the summary statistics for variables of interest for up to 8,222 Compustat industrial firms (utilities, quasi-public and financial firms are excluded) that are included in the LPC-Dealscan database from 1987 to 2013. *Panel A* presents descriptive statistics for the line of credit variables. *LC-to-Cash* is computed for all sample firms, while the cost (*LC Cost*, expressed in percentage points), maturity (*LC Maturity*) and covenants (*Number of Covenants*) variables are only computed for firms exhibiting a non-zero amount of available line of credit during a given year. *Panel B* reports the summary statistics for the customer risk variables. These variables are computed for a subsample of 3,564 unique firms for which at least one major customer is identifiable during a given year. *Panel C* presents summary statistics for the main control variables, i.e. all other firm characteristics of interest. All variables are winsorized at the $5^{th}$ and $95^{th}$ percentiles. Definitions of all line of credit and control variables are reported in Appendix C. Definitions of the customer risk variables are reported in Appendices A and B.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Variables | Mean | Std. Dev. | Min | Median | Max | Firm-Years |
| ***Panel A: LC Variables*** | | | | | | |
| LC-to-Cash | 0.563 | 0.385 | 0.000 | 0.694 | 1.000 | 66429 |
| LC Cost (%) | 2.127 | 1.359 | -0.888 | 2.000 | 12.000 | 18521 |
| LC Maturity (Quarters) | 13.909 | 7.378 | 0 | 12 | 94 | 23529 |
| Nb. of Fin. Covenants | 2.623 | 1.145 | 1 | 3 | 8 | 15045 |
| ***Panel B: Customer Risk Variables*** | | | | | | |
| Customer Risk - Merton | 0.006 | 0.029 | 0.000 | 0.000 | 0.860 | 10132 |
| Customer Risk - CHS | 0.003 | 0.021 | 0.000 | 0.000 | 0.691 | 10730 |
| ***Panel C: Firm Characteristics*** | | | | | | |
| ROA | 0.122 | 0.268 | -1.474 | 0.147 | 0.477 | 63176 |
| Tangibility | 0.331 | 0.242 | 0.005 | 0.269 | 0.877 | 65381 |
| Size | 5.612 | 2.017 | 0.528 | 5.616 | 9.128 | 65552 |
| Net Worth | 0.297 | 0.382 | -1.290 | 0.365 | 0.791 | 65430 |
| Q | 2.151 | 2.146 | 0.689 | 1.460 | 13.858 | 59912 |
| Industry Sales Volatility | 0.046 | 0.036 | 0.000 | 0.036 | 0.383 | 66680 |
| CF Variability | 0.084 | 0.198 | 0.000 | 0.043 | 13.829 | 60707 |
| S&P dummy | 0.293 | 0.455 | 0 | 0 | 1 | 66685 |
| log(Firm Age) | 2.539 | 0.901 | 0.000 | 2.565 | 4.143 | 66631 |
| Beta KMV | 0.677 | 0.485 | 0.467 | 0.647 | 1.457 | 44917 |
| Var KMV | 0.379 | 0.229 | 0.025 | 0.323 | 1.562 | 45316 |
| Receivables | 0.174 | 0.288 | 0.000 | 0.149 | 7.762 | 65648 |
| Doubtful | 0.008 | 0.011 | 0.000 | 0.005 | 0.059 | 51543 |

## Table 3. Univariate Tests - Customer Risk and Lines of Credit

This table presents the univariate comparisons of the main line of credit variables (as described in Appendix C) between a sample of low customer risk and a sample of high customer risk Compustat firms. Low customer risk firms are identified as those ranked in the bottom quartile of the relevant customer risk measure, while high customer risk firms are those ranked in the top quartile of the relevant customer risk measure. Customer risk measures are described in Section 3.2.2 and in Appendices A and B. *Panel A* and *Panel B* report the univariate comparisons of the *LC-to-Cash* variable. In *Panel A*, the bottom and top quartiles of each customer risk variable are drawn from the entire *Customer sample*, which is composed of 3,564 unique industrial Compustat firms. The composition of the *Customer sample* is detailed in Section 3.1. In *Panel B*, the bottom and top quartiles of each customer risk measure are computed based on a subsample of firms within the *Customer sample* that have a non-zero amount of available line of credit during a given year. *Panel C* reports the univariate comparisons of the *Cost* measure. *Panel D* reports the univariate comparisons of the *Number of Covenants* variable. *Panel E* reports the univariate comparisons of the *LC Maturity* variable. ***,** and * indicate significance of t-statistics (chi-squared) for the test of a difference in means (medians) between two subsamples at the 1%, 5% and 10% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Bottom Quartile of customer risk measure | | Top quartile of customer risk measure | | |
| Customer Risk Measures | Obs. | Mean [Median] | Obs. | Mean [Median] | T-stat [Z-stat] |
| ***Panel A: Measured variable = LC-to-Cash(All Observations)*** | | | | | |
| Customer Risk - Merton | 2530 | 0.549 | 2533 | 0.486 | -5.605*** |
| | | [0.673] | | [0.533] | [-4.427***] |
| Customer Risk - CHS | 2681 | 0.543 | 2678 | 0.488 | -5.114*** |
| | | [0.65] | | [0.541] | [-5.055***] |
| Customer Risk - PC | 2301 | 0.563 | 2296 | 0.476 | -7.514*** |
| | | [0.65] | | [0.539] | [-5.16***] |
| ***Panel B: Measured variable = LC-to-Cash (Firms with LC-to-Cash > 0)*** | | | | | |
| Customer Risk - Merton | 1915 | 0.725 | 1824 | 0.675 | -5.21*** |
| | | [0.821] | | [0.769] | [-3.495***] |
| Customer Risk - CHS | 2079 | 0.700 | 1913 | 0.683 | -1.827* |
| | | [0.802] | | [0.785] | [-1.772] |
| Customer Risk - PC | 1777 | 0.730 | 1627 | 0.672 | -5.799*** |
| | | [0.802] | | [0.782] | [-1.861] |

*(Table continued on next page)*

**Table 3. Univariate Tests - Customer Risk And Lines of Credit (Cont'd)**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Bottom Quartile of customer risk measure | | Top quartile of customer risk measure | | |
| Customer risk measures | Obs. | Mean [Median] | Obs. | Mean [Median] | T-stat [Z-stat] |
| ***Panel C: Measured Variable = LC Cost (overall spread)*** | | | | | |
| Customer Risk - Merton | 677 | 2.033 | 619 | 2.513 | 6.421*** |
| | | [1.875] | | [2.5] | [6.907***] |
| Customer Risk - CHS | 739 | 2.126 | 646 | 2.464 | 4.594*** |
| | | [2] | | [2.313] | [4.237***] |
| Customer Risk - PC | 587 | 2.095 | 540 | 2.475 | 4.73*** |
| | | [2] | | [2.375] | [4.983***] |
| ***Panel D: Measured Variable = Number of Financial Covenants*** | | | | | |
| Customer Risk - Merton | 481 | 2.513 | 520 | 2.634 | 1.725* |
| | | [2] | | [2] | [1.064] |
| Customer Risk - CHS | 576 | 2.649 | 509 | 2.628 | -0.31 |
| | | [2.5] | | [3] | [0.022] |
| Customer Risk - PC | 503 | 2.472 | 431 | 2.639 | 2.216** |
| | | [2] | | [3] | [2.109**] |
| ***Panel E: Measured variable = LC Maturity (in quarters)*** | | | | | |
| Customer Risk - Merton | 847 | 14.966 | 790 | 11.493 | -10.501*** |
| | | [16] | | [12] | [-10.423***] |
| Customer Risk - CHS | 948 | 13.006 | 828 | 12.443 | -1.695* |
| | | [12] | | [12] | [-1.605*] |
| Customer Risk - PC | 763 | 13.884 | 694 | 11.939 | -5.551*** |
| | | [14] | | [12] | [-6.116***] |

**Table 4. Customer Risk and The Choice Between Cash and Lines of Credit**

This table reports pooled OLS regression results relating the choice between cash and bank lines of credit and customer risk using a sample of Compustat industrial firms that are included in the LPC-Dealscan database and that reported the existence and identity of at least one major customer, from 1987 to 2013. Major customer identification is described in Section 3.1. The dependent variable is the *LC-to-Cash* measure, as defined in Appendix C and Section 3.2. Definitions of customer risk variables are reported in Appendices A and B, while definitions of all other control variables are reported in Appendix C. Standard errors are corrected for heteroskedasticity and clustering at the supplier firm level (robust t-statistics are reported between brackets). *, **, and *** denote significance at the 10%, 5%, and 1%level, respectively.

| | Dependent Variable: LC-to-Cash | | |
|---|---|---|---|
| Variables | (1) | (2) | (3) |
| Customer Risk - Merton | -0.560*** | | |
| | (-3.281) | | |
| Customer Risk - CHS | | -0.688*** | |
| | | (-3.296) | |
| Customer Risk - PC | | | -0.021*** |
| | | | (-4.009) |
| ROA | 0.048** | 0.039** | 0.048** |
| | (2.499) | (2.111) | (2.475) |
| Tangibility | -0.036 | -0.051 | -0.009 |
| | (-0.742) | (-1.077) | (-0.190) |
| Size | 0.066*** | 0.066*** | 0.065*** |
| | (12.402) | (12.815) | (11.793) |
| Net Worth | -0.074*** | -0.071*** | -0.070*** |
| | (-3.931) | (-3.935) | (-3.657) |
| Q | -0.034*** | -0.033*** | -0.034*** |
| | (-14.567) | (-14.323) | (-13.985) |
| Ind. Sales Vol. | 0.694** | 0.748** | 0.680* |
| | (1.978) | (2.121) | (1.896) |
| CF Variability | -0.116*** | -0.128*** | -0.105** |
| | (-2.605) | (-2.929) | (-2.448) |
| S&P dummy | -0.031 | -0.030 | -0.032 |
| | (-1.568) | (-1.565) | (-1.552) |
| Firm Age | -0.014 | -0.010 | -0.015 |
| | (-1.346) | (-0.937) | (-1.324) |
| Constant | 0.399*** | 0.400*** | 0.405*** |
| | (3.243) | (3.502) | (3.288) |
| Observations | 9,008 | 9,555 | 8,218 |
| R-squared | 0.306 | 0.310 | 0.311 |
| Year dummies | Yes | Yes | Yes |
| Industry dummies | Yes | Yes | Yes |

**Table 5. Customer Risk, Aggregate Risk and The Choice Between Cash and Credit Lines**

This table reports pooled OLS regression results relating the choice between cash and bank lines of credit and customer risk, after controlling for aggregate risk, using a sample of Compustat industrial firms that are included in the LPC-Dealscan database and that reported the existence and identity of at least one major customer, from 1987 to 2013. Major customer identification is described in Section 3.1. The dependent variable is the *LC-to-Cash* measure, as defined in Appendix C and Section 3.2. Aggregrate risk is proxied using the *Beta KMV* and *Var KMV* variables. *Beta KMV* is defined as the unlevered asset beta and is computed using the Merton (1974) model. *Var KMV* is the implied asset volatility obtained when computing *Beta KMV*. Detailed definitions of *Beta KMV* and *Var KMV* are reported in Section 3.2. Definitions of customer risk variables are reported in Appendices A and B, while definitions of all other control variables are reported in Appendix C. Standard errors are corrected for heteroskedasticity and clustering at the supplier firm level (robust t-statistics are reported between brackets). *, **, and *** denote significance at the 10%, 5%, and 1%level, respectively.

*(Table continued on next page).*

**Table 5. Customer Risk, Aggregate Risk and The Choice Between Cash and Credit Lines (Cont'd)**

| | Dependent Variable: LC-to-Cash | | | | | |
|---|---|---|---|---|---|---|
| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
| *Customer Risk Variables* | | | | | | |
| Risk-Merton | -0.685*** | | | -0.662*** | | |
| | (-3.285) | | | (-3.182) | | |
| Risk-CHS | | -0.707*** | | | -0.684*** | |
| | | (-2.676) | | | (-2.582) | |
| Risk-PC | | | -0.024*** | | | -0.023*** |
| | | | (-3.774) | | | (-3.675) |
| *Control Variables* | | | | | | |
| Beta KMV | -0.111*** | -0.114*** | -0.114*** | -0.094*** | -0.096*** | -0.097*** |
| | (-6.100) | (-6.372) | (-5.958) | (-4.946) | (-5.160) | (-4.870) |
| Var KMV | | | | -0.087** | -0.092** | -0.083** |
| | | | | (-2.270) | (-2.498) | (-2.095) |
| ROA | 0.067*** | 0.060*** | 0.071*** | 0.060*** | 0.052** | 0.064*** |
| | (3.033) | (2.848) | (3.129) | (2.689) | (2.472) | (2.810) |
| Tangibility | -0.105** | -0.117** | -0.078 | -0.108** | -0.119** | -0.081 |
| | (-2.082) | (-2.347) | (-1.514) | (-2.149) | (-2.408) | (-1.565) |
| Size | 0.062*** | 0.061*** | 0.060*** | 0.059*** | 0.058*** | 0.057*** |
| | (9.649) | (9.849) | (8.841) | (8.785) | (8.919) | (8.061) |
| Net Worth | -0.024 | -0.020 | -0.029 | -0.024 | -0.021 | -0.030 |
| | (-1.043) | (-0.900) | (-1.239) | (-1.078) | (-0.939) | (-1.268) |
| Q | -0.029*** | -0.028*** | -0.029*** | -0.029*** | -0.028*** | -0.029*** |
| | (-9.267) | (-9.391) | (-9.116) | (-9.371) | (-9.499) | (-9.221) |
| Ind. Sales Vol. | 1.019*** | 1.073*** | 0.989*** | 1.017*** | 1.073*** | 0.990** |
| | (2.725) | (2.836) | (2.583) | (2.717) | (2.834) | (2.579) |
| CF Variability | -0.224*** | -0.246*** | -0.207*** | -0.208*** | -0.230*** | -0.193** |
| | (-2.873) | (-3.270) | (-2.674) | (-2.753) | (-3.150) | (-2.569) |
| S&P dummy | -0.012 | -0.008 | -0.013 | -0.015 | -0.011 | -0.015 |
| | (-0.563) | (-0.401) | (-0.553) | (-0.691) | (-0.533) | (-0.666) |
| Firm Age | -0.018 | -0.015 | -0.016 | -0.019 | -0.016 | -0.017 |
| | (-1.500) | (-1.282) | (-1.259) | (-1.615) | (-1.409) | (-1.353) |
| Constant | 0.513*** | 0.513*** | 0.514*** | 0.554*** | 0.560*** | 0.553*** |
| | (3.727) | (3.912) | (3.763) | (4.051) | (4.283) | (4.083) |
| Observations | 6,765 | 7,158 | 6,154 | 6,765 | 7,158 | 6,154 |
| R-squared | 0.295 | 0.298 | 0.302 | 0.296 | 0.299 | 0.303 |
| Ind. dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 6. Customer Risk, Trade Credit and The Choice Between Cash and Lines of Credit**

This table reports pooled OLS regression results relating the choice between cash and bank lines of credit and both customer risk, after controlling for various dimensions of trade credit, using a sample of Compustat industrial firms that are included in the LPC-Dealscan database and that reported the existence and identity of at least one major customer, from 1987 to 2013. Major customer identification is described in Section 3.1. The dependent variable is the *LC-to-Cash* measure, as defined in Section 3.2. Trade credit is proxied using the *Receivables* and *Doubtful* variables. *Receivables* is defined as the ratio of annual total account receivables to aggregated annual sales. *Doubtful* is the annual ratio of estimated doubtful accounts to aggregated sales. Detailed definitions of *Receivables* and *Doubtful* are reported in Section 3.2. Definitions of customer risk variables are reported in Appendices A and B, while definitions of all other control variables are reported in Appendix C. Standard errors are corrected for heteroskedasticity and clustering at the supplier firm level (robust t-statistics are reported between brackets). *, **, and *** denote significance at the 10%, 5%, and 1%level, respectively.

*(Table continued on next page)*

**Table 6. Customer Risk, Trade Credit and The Choice Between Cash and Lines of Credit (Cont'd)**

| | Dependent Variable: LC-to-Cash | | |
|---|---|---|---|
| Variables | (1) | (2) | (3) |
| Customer Risk - Merton | -0.731*** | | |
| | (-3.498) | | |
| Customer Risk - CHS | | -0.701*** | |
| | | (-2.585) | |
| Customer Risk - PC | | | -0.022*** |
| | | | (-3.541) |
| Receivables | -0.166** | -0.145* | -0.204** |
| | (-1.999) | (-1.873) | (-2.235) |
| Doubtful | -0.934 | -0.426 | -0.510 |
| | (-0.950) | (-0.462) | (-0.507) |
| Beta KMV | -0.112*** | -0.119*** | -0.114*** |
| | (-5.703) | (-6.188) | (-5.582) |
| ROA | 0.064** | 0.065*** | 0.069** |
| | (2.442) | (2.675) | (2.578) |
| Tangibility | -0.118** | -0.128** | -0.102* |
| | (-2.032) | (-2.287) | (-1.730) |
| Size | 0.067*** | 0.066*** | 0.065*** |
| | (9.744) | (9.938) | (8.969) |
| Net Worth | -0.035 | -0.033 | -0.040 |
| | (-1.363) | (-1.347) | (-1.527) |
| Q | -0.032*** | -0.031*** | -0.032*** |
| | (-9.493) | (-9.684) | (-9.423) |
| Ind. Sales Vol. | 1.258*** | 1.341*** | 1.242*** |
| | (3.141) | (3.388) | (3.024) |
| CF Variability | -0.183** | -0.217*** | -0.171** |
| | (-2.310) | (-2.780) | (-2.153) |
| S&P dummy | -0.028 | -0.025 | -0.026 |
| | (-1.192) | (-1.106) | (-1.033) |
| Firm Age | -0.014 | -0.012 | -0.013 |
| | (-1.052) | (-0.946) | (-0.922) |
| Constant | 0.429*** | 0.400** | 0.435*** |
| | (2.706) | (2.457) | (2.709) |
| Observations | 5,472 | 5,783 | 4,979 |
| R-squared | 0.298 | 0.304 | 0.303 |
| Industry dummies | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes |

**Table 7. Instrumental Variable Regressions**

This table reports the results from 2-Stage Least Square regressions relating the choice between cash and lines of credit to customer risk measures and a set of control variables using instrumental variables. The sample consists of Compustat industrial firms, that are included in the LPC-Dealscan database and that reported the existence and identity of at least one major customer, from 1987 to 2013. Major customer identification is described in Section 3.1. I use the predicted values from the first-stage in the second-stage regressions. Columns (1), (3) and (5) present first-stage results, while columns (2), (4) and (6) present second-stage results. In columns (1) and (2), customer risk is measured using the Merton (1974) structural model. In columns(3) and (4), customer risk is measured using Campbell, Hilsher and Szilagyi's (2008) - hereafter CHS - hazard model. In columns (5) and (6), customer risk is measured as the first principal component resulting from a principal component (PC) analysis between Altman's (1968) modified weighted average Z-score of a supplier firm's major customers, Merton's based customer risk measure and CHS-based customer risk measure. The dependent variable in columns (1), (3) and (5) is the relevant customer risk measure. In columns (2), (4) and (6), the dependent variable is the *LC-to-Cash* measure, as defined in Appendix C. Control variables are included following Equation 4, as defined in Section 4.1. Definitions of all control variables are reported in Appendix C. Definitions of the customer risk variables are reported in Appendices A and B. Standard errors are corrected for heteroskedasticity and clustering at the supplier firm level (robust t-statistics are reported between brackets). *, **, and *** denote significance at the 10%, 5%, and 1%level, respectively.

*(Table continued on next page)*

**Table 7. Instrumental Variable Regressions (Cont'd)**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Merton Model | | CHS Model | | PC Analysis | |
| Variables | $1^{st}$ Stage | $2^{nd}$ Stage | $1^{st}$ Stage | $2^{nd}$ Stage | $1^{st}$ Stage | $2^{nd}$ Stage |
| *Instrumental Variables* | | | | | | |
| Cust. Idio. Vol. | 0.217** | | 0.086* | | 6.865** | |
| | (1.973) | | (1.813) | | (2.294) | |
| Cust. LC Dummy | -0.010* | | -0.008* | | -0.578** | |
| | (-1.949) | | (-1.818) | | (-2.282) | |
| *Customer Risk Variables* | | | | | | |
| Risk - Merton | | -0.727* | | | | |
| | | (-1.681) | | | | |
| Risk - CHS | | | | -3.597* | | |
| | | | | (-1.936) | | |
| Risk - First PC | | | | | | -0.029* |
| | | | | | | (-1.774) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 755 | 755 | 777 | 777 | 722 | 722 |
| Log Likelihood | . | 72.10 | . | 28.33 | . | 58.69 |
| $1^{st}$-stage F-stat | 4.609 | . | 1.711 | . | 5.280 | . |
| Weak IV robust test$^{(1)}$ | . | 0.641 | . | 0.399 | . | 0.657 |
| Underid. stat.$^{(2)}$ | . | 9.654 | . | 6.215 | . | 14.37 |
| Overid. test $^{(3)}$ | . | 0.589 | . | 0.781 | . | 0.906 |
| Industry dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes |

$^{(1)}$Anderson-Rubin weak IV robust test

$^{(2)}$Kleibergen-Paap rank LM statistic

$^{(3)}$P-value of the Hansen J-statistic

**Table 8. Customer Risk and The Cost of Lines of Credit**

This table reports pooled OLS regression results relating the cost of lines of credit and customer risk, using a sample of Compustat industrial firms that are included in the LPC-Dealscan database and that reported the existence and identity of at least one major customer, from 1987 to 2013. Major customer identification is described in Section 3.1. The dependent variable is the natural logarithm of *LC Cost*, measured as the overall spread paid on newly opened lines of credit. Appendix C and Section 3.2 present a detailed definition of LC Cost. Definitions of customer risk variables are reported in Appendices A and B, while definitions of all other control variables are reported in Appendix C. Standard errors are corrected for heteroskedasticity and clustering at the supplier firm level (robust t-statistics are reported between brackets). *, **, and *** denote significance at the 10%, 5%, and 1%level, respectively.

*(Table continued on next page)*

Table 8. Customer Risk and The Cost of Lines of Credit (Cont'd)

| | Dependent Var. = Log(LC Cost) | | | Dependent Var. = LC Cost | | |
|---|---|---|---|---|---|---|
| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
| *Customer Risk Variables* | | | | | | |
| Risk - Merton | 0.704 | | | 1.877 | | |
| | (1.361) | | | (1.643) | | |
| Risk - CHS | | 0.932** | | | 2.183** | |
| | | (2.144) | | | (2.298) | |
| Risk - PC | | | 0.028** | | | 0.073*** |
| | | | (2.370) | | | (2.730) |
| *Control Variables* | | | | | | |
| Beta KMV | 0.039 | 0.063 | 0.074 | -0.062 | -0.059 | -0.024 |
| | (0.870) | (1.411) | (1.594) | (-0.815) | (-0.780) | (-0.307) |
| Leverage | 0.677*** | 0.694*** | 0.768*** | 0.823*** | 0.899*** | 0.952*** |
| | (5.265) | (5.573) | (6.101) | (3.749) | (4.094) | (4.516) |
| LIBOR | -0.020 | -0.014 | -0.013 | -0.045 | -0.030 | -0.042 |
| | (-0.680) | (-0.489) | (-0.420) | (-0.797) | (-0.526) | (-0.701) |
| New LC | -0.407*** | -0.389*** | -0.437*** | -0.652*** | -0.625*** | -0.702*** |
| | (-8.896) | (-8.423) | (-9.512) | (-6.375) | (-6.282) | (-6.386) |
| ROA | -0.356*** | -0.333*** | -0.371*** | -0.862*** | -0.814*** | -0.889*** |
| | (-4.070) | (-3.903) | (-3.893) | (-4.564) | (-4.262) | (-4.317) |
| Tangibility | -0.149 | -0.168 | -0.204* | 0.005 | -0.034 | -0.046 |
| | (-1.285) | (-1.544) | (-1.803) | (0.036) | (-0.277) | (-0.350) |
| Size | -0.319*** | -0.315*** | -0.322*** | -0.437*** | -0.436*** | -0.439*** |
| | (-22.559) | (-23.049) | (-21.745) | (-22.313) | (-23.320) | (-21.522) |
| Net Worth | -0.241*** | -0.240*** | -0.140 | -0.658*** | -0.623*** | -0.489*** |
| | (-2.716) | (-2.810) | (-1.640) | (-4.120) | (-3.918) | (-3.245) |
| Q | -0.100*** | -0.100*** | -0.104*** | -0.139*** | -0.137*** | -0.143*** |
| | (-8.014) | (-8.224) | (-8.417) | (-7.010) | (-7.143) | (-7.558) |
| Ind. Sales Vol. | -0.003 | -0.160 | 0.169 | -1.459 | -1.677* | -1.533 |
| | (-0.004) | (-0.207) | (0.213) | (-1.518) | (-1.773) | (-1.544) |
| CF Variability | 1.119*** | 1.156*** | 1.150*** | 2.504*** | 2.544*** | 2.613*** |
| | (4.684) | (5.064) | (4.874) | (4.817) | (5.256) | (4.903) |
| Constant | 2.689*** | 2.516*** | 2.618*** | 4.823*** | 4.649*** | 4.709*** |
| | (8.304) | (7.664) | (7.585) | (8.259) | (7.945) | (7.590) |
| Observations | 1,802 | 1,901 | 1,619 | 1,802 | 1,901 | 1,619 |
| R-squared | 0.633 | 0.629 | 0.650 | 0.535 | 0.533 | 0.547 |
| Ind. dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 9. Customer Risk and Credit Lines Covenants**

This table reports pooled OLS regression results relating customer risk and the number of covenants attached to lines of credit agreements, using a sample of Compustat industrial firms that are included in the LPC-Dealscan database and that reported the existence and identity of at least one major customer, from 1987 to 2013. Major customer identification is described in Section 3.1. The dependent variable is the natural logarithm of the number of financial and net worth covenants attached to credit lines contracts reported in the LPC-Dealscan database. Panel A presents regressions estimates computed for the entire sample. In Panel B, firms are sorted depending on whether their EBITDA is above or below the median of the overall yearly EBITDA distribution. Definitions of customer risk variables are reported in Appendices A and B. *New LC* is the total amount of lines of credit raised during a given year scaled total non-cash assets, *LIBOR* is the annualized weighted average level of the LIBOR in the quarter during which a line of credit was raised and *Leverage* is past book leverage. Definitions of all other control variables are reported in Appendix C. Standard errors are corrected for heteroskedasticity and clustering at the supplier firm level (robust t-statistics are reported between brackets). *, **, and *** denote significance at the 10%, 5%, and 1%level, respectively.

*(Table continued on next page)*

**Table 9. Customer Risk and Credit Lines Covenants (Cont'd)**

***Panel A: Baseline Regression Specification***

| | Dependent Variable = Log(1+ Nb of covenants) | | |
|---|---|---|---|
| Variables | (1) | (2) | (3) |
| Customer Risk - Merton | -0.300 | | |
| | (-1.106) | | |
| Customer Risk - CHS | | -0.840*** | |
| | | (-2.673) | |
| Customer Risk - First PC | | | -0.014 |
| | | | (-1.508) |
| Beta KMV | 0.018 | 0.032 | 0.021 |
| | (0.667) | (1.196) | (0.753) |
| Leverage | 0.117 | 0.145* | 0.144 |
| | (1.353) | (1.751) | (1.595) |
| LIBOR | -0.032 | -0.033 | -0.031 |
| | (-1.517) | (-1.634) | (-1.435) |
| New LC | -0.044 | -0.035 | -0.041 |
| | (-1.284) | (-1.081) | (-1.103) |
| ROA | 0.181*** | 0.163*** | 0.171*** |
| | (3.276) | (3.326) | (2.984) |
| Tangibility | -0.012 | -0.032 | -0.021 |
| | (-0.163) | (-0.430) | (-0.260) |
| Size | -0.067*** | -0.063*** | -0.066*** |
| | (-7.806) | (-7.569) | (-7.318) |
| Net Worth | 0.047 | 0.067 | 0.062 |
| | (0.816) | (1.226) | (1.006) |
| Q | -0.023*** | -0.023*** | -0.024*** |
| | (-3.857) | (-4.169) | (-3.913) |
| Industry Sales Volatility | -0.167 | -0.100 | -0.187 |
| | (-0.381) | (-0.231) | (-0.408) |
| CF Variability | -0.210* | -0.117 | -0.178 |
| | (-1.694) | (-0.959) | (-1.459) |
| Constant | 1.669*** | 1.491*** | 1.639*** |
| | (4.968) | (4.308) | (4.916) |
| Observations | 1,413 | 1,499 | 1,298 |
| R-squared | 0.264 | 0.252 | 0.271 |
| Industry dummies | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes |

*(Table continued on next page)*

**Table 9. Customer Risk and Credit Lines Covenants (Cont'd)**

***Panel B: Customer Risk, Financial Covenants and Operating Cash-Flows***

| | Dependent Variable = Log(1+Nb of Covenants) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Low | High | Low | High | Low | High |
| Variables | EBITDA | EBITDA | EBITDA | EBITDA | EBITDA | EBITDA |
| *Customer Risk Variables* | | | | | | |
| Risk - Merton | -0.348 | -0.380 | | | | |
| | (-1.240) | (-0.326) | | | | |
| Risk - CHS | | | -0.994*** | 1.093 | | |
| | | | (-4.018) | (0.930) | | |
| Risk - PC | | | | | -0.021** | 0.016 |
| | | | | | (-2.462) | (0.500) |
| *Control Variable(s)* | | | | | | |
| ROA | 0.154** | -0.126 | 0.139** | -0.096 | 0.154** | -0.117 |
| | (2.551) | (-0.969) | (2.547) | (-0.784) | (2.517) | (-0.859) |
| Other Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 539 | 874 | 582 | 917 | 501 | 797 |
| R-squared | 0.263 | 0.400 | 0.247 | 0.390 | 0.293 | 0.392 |
| Ind. dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes |

## Table 10. Customer Risk and Non Financial Covenants

### *Panel A: Univariate Statistics*

This table presents the univariate comparisons of the mean yearly number of various non financial covenants attached to credit line contracts between a sample of low customer risk and a sample of high customer risk Compustat firms. All covenants are defined in Appendix C. Low customer risk firms are identified as those ranked in the bottom quartile of the relevant customer risk measure, while high customer risk firms are those ranked in the top quartile of the relevant customer risk measure. Customer risk measures are described in Section 3.2.2 and in Appendices A and B. ***,** and * indicate significance of t-statistics for the test of a difference in means between two subsamples at the 1%, 5% and 10% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Low customer risk | | High customer risk | | |
| Variables | Obs | Mean | Obs | Mean | T-stat |
| *Merton-based Customer Risk Measure* | | | | | |
| Borrowing Base | 847 | 0.165 | 790 | 0.295 | 6.333*** |
| Dividend Restrictions | 490 | 0.811 | 505 | 0.850 | 1.664* |
| Asset Sales Sweep | 237 | 0.711 | 185 | 0.892 | 4.868*** |
| Equity Issuance Sweep | 184 | 0.514 | 144 | 0.729 | 4.131*** |
| Debt Issuance Sweep | 203 | 0.574 | 152 | 0.789 | 4.502*** |
| *CHS-based Customer Risk Measure* | | | | | |
| Borrowing Base | 948 | 0.220 | 828 | 0.270 | 2.444** |
| Dividend Restrictions | 571 | 0.806 | 515 | 0.852 | 2.025** |
| Asset Sales Sweep | 254 | 0.752 | 210 | 0.760 | 0.189 |
| Equity Issuance Sweep | 220 | 0.561 | 171 | 0.599 | 0.761 |
| Debt Issuance Sweep | 219 | 0.594 | 184 | 0.658 | 1.334 |
| *PCA-based Customer Risk Measure* | | | | | |
| Borrowing Base | 763 | 0.256 | 694 | 0.276 | 0.871 |
| Dividend Restrictions | 504 | 0.791 | 422 | 0.840 | 1.949* |
| Asset Sales Sweep | 185 | 0.816 | 158 | 0.924 | 2.969*** |
| Equity Issuance Sweep | 135 | 0.673 | 130 | 0.837 | 3.15*** |
| Debt Issuance Sweep | 159 | 0.715 | 135 | 0.874 | 3.396*** |

*(Table continued on next page)*

**Table 10. Customer Risk and Non Financial Covenants (Cont'd)**

***Panel B: Non Financial Covenants, Customer Risk and Operating Cash-Flows***

This table reports pooled OLS regression results relating customer risk and the number of non financial covenants attached to lines of credit agreements, using a sample of Compustat industrial firms that are included in the LPC-Dealscan database and that reported the existence and identity of at least one major customer, from 1987 to 2013. Major customer identification is described in Section 3.1. The dependent variable is the natural logarithm of the number of non financial covenants attached to credit lines contracts reported in the LPC-Dealscan database. Firms are sorted depending on whether their EBITDA is above or below the median of the overall yearly EBITDA distribution. Definitions of customer risk variables are reported in Appendices A and B. *New LC* is the total amount of lines of credit raised during a given year scaled total non-cash assets, *LIBOR* is the annualized weighted average level of the LIBOR in the quarter during which a line of credit was raised and *Leverage* is past book leverage. Definitions of all other control variables are reported in Appendix C. Standard errors are corrected for heteroskedasticity and clustering at the supplier firm level (robust t-statistics are reported between brackets). *, **, and *** denote significance at the 10%, 5%, and 1%level, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Dependent Variable: Log(1 + Nb Non Financial Covenants) | | | | | |
| Variables | Low EBITDA | High EBITDA | Low EBITDA | High EBITDA | Low EBITDA | High EBITDA |
| *Customer Risk Variables* | | | | | | |
| Risk - Merton | 1.727* | -5.181 | | | | |
| | (1.698) | (-0.841) | | | | |
| Risk - CHS | | | 1.173* | -5.701 | | |
| | | | (1.920) | (-1.089) | | |
| Risk - First PC | | | | | 0.012 | -0.178 |
| | | | | | (0.949) | (-1.380) |
| *Control Variable(s)* | | | | | | |
| ROA | -0.281*** | -0.117 | -0.150* | -0.059 | -0.415** | -0.202 |
| | (-2.822) | (-0.345) | (-1.842) | (-0.174) | (-2.193) | (-0.571) |
| Other Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 159 | 247 | 171 | 257 | 144 | 208 |
| R-squared | 0.728 | 0.675 | 0.710 | 0.650 | 0.703 | 0.699 |
| Industry dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 11. Propensity Score Matched Sample Analysis**

This table reports results relating the choice between cash and lines of credit to customer risk measures and a set of control variables for a propensity score matched sample using Compustat industrial firms that are included in the LPC-Dealscan database and that reported the existence and identity of at least one major customer, from 1987 to 2013. Major customer identification is described in Section 3.1. The matching procedure is described in Section 5.1. Panel A presents pre- and post-matching regression results of customer risk dummy variables on various control variables. In each regression specification, the dependent variable is a dummy variable that is equal to one if a supplier firm aces low customer risk, and zero if it faces high customer risk. Low customer risk firms are identified as those ranked in the bottom quartile of the relevant customer risk measure, while high customer risk firms are those ranked in the top quartile of the relevant customer risk measure. In columns (1) and (2), customer risk is measured using the Merton (1974) structural model (Merton Sample). In columns(3) and (4), customer risk is measured using Campbell, Hilsher and Szilagyi's (2008) - hereafter CHS - hazard model (CHS Sample). In columns (5) and (6), customer risk is measured as the first principal component resulting from a principal component (PC) analysis between Altman's (1968) modified weighted average Z-score of a supplier firm's major customers, Merton's based customer risk measure and CHS-based customer risk measure (PCA Sample). Columns (1), (3) and (5) of Panel A show the first-stage marginal effects from a probit regression used to compute the propensity scores for the matching procedure. Columns (2), (4) and (6) of Panel A show the marginal effects from the probit regressions in columns (1), (3) and (5), respectively, using the appropriate subsample of matched suppliers. Panel B reports the univariate statistics comparing the mean propensity scores and characteristics of supplier for each appropriate matched subsamples. Panel C reports multivariate results relating the choice between cash and lines of credit to customer risk for each matched sample. The dependent variable is *LC-to-Cash*, as defined in Appendix C and Section 3.2. Panel D reports multivariate results relating the cost of bank lines of credit to customer risk for each matched sample. The dependent variable is the natural logarithm of *LC Cost*, as defined in Appendix C and Section 3.2.

Definitions of customer risk variables are reported in Appendices A and B. Definitions of all other control variables are reported in Appendix C. Standard errors are corrected for heteroskedasticity and clustering at the supplier firm level (robust t-statistics are reported between brackets). *, **, and *** denote significance at the 10%, 5%, and 1%level, respectively.

*(Table continued on next page)*

**Table 11. Propensity Score Matched Sample Analysis (Cont'd)**

***Panel A: Pre-Matching Propensity Score Regression and Post-Matching Diagnosis Regression***

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Dependent Variable: $\mathbb{1}_{Low\ Customer\ Risk}$ | | | | | |
| | Merton Model | | CHS Model | | PC Analysis | |
| Variables | Pre-Matching | Post-Matching | Pre-Matching | Post-Matching | Pre-Matching | Post-Matching |
| Leverage | -0.929** | 0.030 | -0.032 | -0.093 | 0.128 | 0.277 |
| | (-2.095) | (0.066) | (-0.089) | (-0.248) | (0.247) | (0.504) |
| Cash | -1.380*** | -0.090 | -1.295*** | -0.145 | -0.901* | -0.129 |
| | (-3.104) | (-0.175) | (-3.475) | (-0.352) | (-1.691) | (-0.226) |
| Beta KMV | 0.215 | 0.080 | 0.227* | 0.059 | -0.160 | 0.042 |
| | (1.595) | (0.553) | (1.889) | (0.435) | (-1.074) | (0.259) |
| Var KMV | -3.503*** | -0.254 | -0.450** | -0.013 | -1.575*** | 0.036 |
| | (-12.527) | (-0.822) | (-2.002) | (-0.049) | (-5.535) | (0.108) |
| ROA | -0.053 | -0.018 | 0.360** | 0.159 | -0.592** | 0.012 |
| | (-0.249) | (-0.073) | (2.020) | (0.840) | (-2.282) | (0.046) |
| Tangibility | -0.354 | -0.054 | 0.108 | -0.191 | -1.182*** | 0.043 |
| | (-1.379) | (-0.198) | (0.501) | (-0.816) | (-3.650) | (0.123) |
| Size | -0.140*** | -0.007 | 0.048 | -0.013 | 0.068 | 0.008 |
| | (-3.072) | (-0.135) | (1.200) | (-0.313) | (1.259) | (0.136) |
| Net Worth | -0.207 | 0.092 | 0.352* | -0.006 | 0.368 | 0.205 |
| | (-0.830) | (0.337) | (1.805) | (-0.030) | (1.226) | (0.681) |
| Ind. Sales Vol. | -7.712*** | -0.140 | -3.406* | -1.732 | -5.784** | -0.342 |
| | (-3.581) | (-0.071) | (-1.951) | (-0.922) | (-2.271) | (-0.128) |
| CF Variability | -0.680 | -0.073 | 0.012 | -0.243 | -0.094 | 0.255 |
| | (-1.232) | (-0.135) | (0.026) | (-0.470) | (-0.179) | (0.501) |
| S&P dummy | 0.217 | -0.007 | 0.012 | -0.031 | 0.185 | 0.011 |
| | (1.481) | (-0.040) | (0.098) | (-0.232) | (1.006) | (0.052) |
| Firm Age | 0.287*** | -0.003 | 0.041 | 0.053 | 0.304*** | -0.018 |
| | (3.463) | (-0.032) | (0.609) | (0.730) | (2.947) | (-0.162) |
| Constant | 2.085*** | 0.006 | -0.352 | 0.079 | 0.074 | -0.219 |
| | (4.610) | (0.012) | (-0.906) | (0.187) | (0.135) | (-0.367) |
| Observations | 3,424 | 2,034 | 3,511 | 2,802 | 3,121 | 1,916 |
| Observations | 3,422 | 2,340 | 3,505 | 2,506 | 3,117 | 1,894 |
| Pseudo R-squared | 0.096 | 0.001 | 0.023 | 0.001 | 0.067 | 0.001 |
| Industry dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes |

*(Table continued on next page)*

**Table 11. Propensity Score Matched Sample Analysis (Cont'd)**

***Panel B: Differences in Propensity Scores and Observed Variables***

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Low Customer Risk | | High Customer Risk | | |
| Variables | Obs | Mean | Obs | Mean | T-stat |
| *Merton-based Customer Risk Measure* | | | | | |
| Propensity score | 1170 | 0.522 | 1170 | 0.527 | -0.643 |
| Leverage | 1170 | 0.261 | 1170 | 0.258 | 0.376 |
| Cash | 1170 | 0.127 | 1170 | 0.13 | -0.558 |
| Beta KMV | 1170 | 0.723 | 1170 | 0.738 | -0.82 |
| Var KMV | 1170 | 0.386 | 1170 | 0.383 | 0.446 |
| ROA | 1170 | 0.133 | 1170 | 0.133 | -0.013 |
| Tangibility | 1170 | 0.323 | 1170 | 0.322 | 0.168 |
| Size | 1170 | 5.784 | 1170 | 5.796 | -0.156 |
| Net worth | 1170 | 0.361 | 1170 | 0.364 | -0.213 |
| Q | 1170 | 1.987 | 1170 | 2.117 | -1.583 |
| Industry Sales Volatility | 1170 | 0.042 | 1170 | 0.041 | 0.222 |
| CF Variability | 1170 | 0.08 | 1170 | 0.08 | -0.028 |
| S&P dummy | 1170 | 0.374 | 1170 | 0.38 | -0.298 |
| Firm Age | 1170 | 2.71 | 1170 | 2.71 | 0.001 |
| *CHS-based Customer Risk Measure* | | | | | |
| Propensity score | 1253 | 0.507 | 1253 | 0.513 | -0.906 |
| Leverage | 1253 | 0.249 | 1253 | 0.244 | 0.655 |
| Cash | 1253 | 0.141 | 1253 | 0.139 | 0.245 |
| Beta KMV | 1253 | 0.734 | 1253 | 0.743 | -0.544 |
| Var KMV | 1253 | 0.423 | 1253 | 0.422 | 0.122 |
| ROA | 1253 | 0.114 | 1253 | 0.125 | -1.024 |
| Tangibility | 1253 | 0.321 | 1253 | 0.314 | 0.788 |
| Size | 1253 | 5.645 | 1253 | 5.659 | -0.183 |
| Net worth | 1253 | 0.363 | 1253 | 0.372 | -0.707 |
| Q | 1253 | 2.147 | 1253 | 2.138 | 0.109 |
| Industry Sales Volatility | 1253 | 0.042 | 1253 | 0.041 | 0.864 |
| CF Variability | 1253 | 0.089 | 1253 | 0.086 | 0.678 |
| S&P dummy | 1253 | 0.346 | 1253 | 0.35 | -0.21 |
| Firm Age | 1253 | 2.643 | 1253 | 2.677 | -1.078 |

*(Table continued on next page)*

**Table 11. Propensity Score Matched Sample Analysis (Cont'd)**

***Panel B: Differences in Propensity Scores and Observed Variables (Cont'd)***

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Low Customer Risk | | High Customer Risk | | |
| Variables | Obs | Mean | Obs | Mean | T-stat |
| *PCA-based Customer Risk Measure* | | | | | |
| Propensity score | 947 | 0.492 | 947 | 0.498 | -0.825 |
| Leverage | 947 | 0.246 | 947 | 0.25 | -0.409 |
| Cash | 947 | 0.153 | 947 | 0.147 | 0.707 |
| Beta KMV | 947 | 0.751 | 947 | 0.758 | -0.326 |
| Var KMV | 947 | 0.427 | 947 | 0.426 | 0.099 |
| ROA | 947 | 0.104 | 947 | 0.11 | -0.514 |
| Tangibility | 947 | 0.317 | 947 | 0.324 | -0.672 |
| Size | 947 | 5.574 | 947 | 5.611 | -0.425 |
| Net worth | 947 | 0.361 | 947 | 0.372 | -0.703 |
| Q | 947 | 2.105 | 947 | 2.107 | -0.018 |
| Industry Sales Volatility | 947 | 0.044 | 947 | 0.043 | 0.376 |
| CF Variability | 947 | 0.093 | 947 | 0.094 | -0.231 |
| S&P dummy | 947 | 0.338 | 947 | 0.34 | -0.097 |
| Firm Age | 947 | 2.624 | 947 | 2.61 | 0.412 |

*(Table continued on next page)*

**Table 11. Propensity Score Matched Sample Analysis (Cont'd)**

***Panel C: LC-to-Cash Regressions - Matched Sample***

| | (1) | (2) | (3) |
|---|---|---|---|
| | Dependent Variable: LC-to-Cash | | |
| Variables | Merton Sample | CHS Sample | PCA Sample |
| Customer Risk - Merton | -0.513* | | |
| | (-1.843) | | |
| Customer Risk - CHS | | -0.747*** | |
| | | (-3.817) | |
| Customer Risk - First PC | | | -0.019** |
| | | | (-2.196) |
| Beta KMV | -0.075*** | -0.120*** | -0.172*** |
| | (-3.005) | (-5.238) | (-6.255) |
| ROA | 0.071** | 0.007 | 0.083** |
| | (2.045) | (0.226) | (2.309) |
| Tangibility | -0.078 | -0.171*** | -0.049 |
| | (-1.196) | (-2.897) | (-0.621) |
| Size | 0.066*** | 0.058*** | 0.070*** |
| | (7.798) | (8.177) | (7.576) |
| Net Worth | -0.030 | -0.039 | -0.039 |
| | (-0.958) | (-1.444) | (-1.133) |
| Q | -0.031*** | -0.028*** | -0.021*** |
| | (-6.447) | (-7.351) | (-4.723) |
| Industry Sales Volatility | 1.375*** | 0.503 | 0.910* |
| | (2.791) | (1.150) | (1.818) |
| MMCF | -0.112 | -0.320*** | -0.219** |
| | (-1.079) | (-3.323) | (-2.208) |
| S&P dummy | -0.013 | 0.024 | -0.058* |
| | (-0.452) | (0.994) | (-1.775) |
| Firm Age | -0.015 | -0.027** | -0.030 |
| | (-1.022) | (-2.020) | (-1.629) |
| Constant | 0.286* | 0.425*** | 0.481** |
| | (1.802) | (2.775) | (1.979) |
| Observations | 2,340 | 2,506 | 1,894 |
| R-squared | 0.310 | 0.311 | 0.332 |
| Industry dummies | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes |

## Table 11. Propensity Score Matched Sample Analysis (Cont'd)

### *Panel D: LC Cost Regressions - Matched Sample*

| | (1) | (2) | (3) |
|---|---|---|---|
| | Dependent Variable: Log(LC Cost) | | |
| Variables | Merton Sample | CHS Sample | PCA Sample |
| Customer Risk - Merton | 1.511 | | |
| | (1.159) | | |
| Customer Risk - CHS | | 0.999** | |
| | | (2.146) | |
| Customer Risk - First PC | | | 0.032** |
| | | | (2.428) |
| Beta KMV | 0.028 | 0.094 | 0.189** |
| | (0.250) | (1.089) | (1.991) |
| Leverage | 0.709* | 0.892*** | 1.030*** |
| | (1.927) | (4.308) | (4.436) |
| LIBOR | -0.141 | 0.003 | -0.036 |
| | (-0.814) | (0.042) | (-0.488) |
| New LC | -0.426*** | -0.464*** | -0.389*** |
| | (-4.640) | (-7.697) | (-3.927) |
| ROA | -0.817** | -0.413** | -0.457*** |
| | (-2.038) | (-2.515) | (-2.886) |
| Tangibility | -0.243 | -0.157 | -0.389* |
| | (-0.949) | (-0.881) | (-1.893) |
| Size | -0.305*** | -0.294*** | -0.300*** |
| | (-8.320) | (-13.014) | (-10.178) |
| Net Worth | -0.090 | -0.164 | -0.062 |
| | (-0.373) | (-1.272) | (-0.410) |
| Q | -0.064* | -0.080*** | -0.121*** |
| | (-1.735) | (-4.617) | (-4.656) |
| Industry Sales Volatility | 0.301 | 0.691 | 0.260 |
| | (0.120) | (0.414) | (0.183) |
| MMCF | 1.054 | 1.056*** | 0.855* |
| | (1.483) | (2.841) | (1.812) |
| Constant | 3.281** | 1.755*** | 2.644*** |
| | (2.271) | (3.009) | (3.944) |
| Observations | 192 | 540 | 342 |
| R-squared | 0.731 | 0.592 | 0.665 |
| Industry dummies | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes |

**Table 12. Major Customers and The Choice Between Cash and Lines of Credit**

This table reports pooled OLS regression results relating customer risk and both the choice between cash and lines of credit, and the cost of bank credit lines, using a sample of Compustat industrial firms that are included in the LPC-Dealscan database and that reported the existence and identity of at least one major customer, from 1987 to 2013. The initial major customer identification procedure is described in Section 3.1. The sample is further restricted to supplier firms reporting only customers that account for 10% or more of their annual aggregate sales (i.e. that are subject to mandatory disclosure, as defined by SFAS No. 14 an No.131). In columns (1) to (3), the dependent variable is the *LC-to-Cash* measure, as defined in Appendix C and Section 3.2. Control variables are included following Equation 4, as defined in Section 4.1. In columns (4) to (6), the dependent variable is the natural logarithm of *LC Cost*, measured as the overall spread paid on newly opened lines of credit. Appendix C and Section 3.2 present a detailed definition of LC Cost. Control variables are included following Equation 5, as defined in Section 4.2. Definitions of customer risk variables are reported in Appendices A and B. Definitions of all control variables are reported in Appendix C. Standard errors are corrected for heteroskedasticity and clustering at the supplier firm level (robust t-statistics are reported between brackets). *, **, and *** denote significance at the 10%, 5%, and 1%level, respectively.

| | Dependent variable = LC-to-Cash | | | Dependent variable = Ln(LC Cost) | | |
|---|---|---|---|---|---|---|
| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
| Customer Risk - Merton | -0.705*** | | | 0.948 | | |
| | (-3.254) | | | (1.532) | | |
| Customer Risk - CHS | | -0.644** | | | 1.058** | |
| | | (-2.285) | | | (2.270) | |
| Customer Risk - First PC | | | -0.021*** | | | 0.034*** |
| | | | (-3.488) | | | (2.614) |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,047 | 5,260 | 4,424 | 1,325 | 1,378 | 1,147 |
| R-squared | 0.320 | 0.324 | 0.330 | 0.622 | 0.618 | 0.651 |
| Ind. dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 13. Customer Risk, Customer Concentration and The Choice Between Cash and Lines of Credit**

This table reports pooled OLS regression results relating customer risk and both the choice between cash and lines of credit, and the cost of bank credit lines, after controlling for customer-base concentration. The sample is composed of Compustat industrial firms that are included in the LPC-Dealscan database and that reported the existence and identity of at least one major customer, from 1987 to 2013. Major customer identification is described in Section 3.1. In columns (1) to (3), the dependent variable is the *LC-to-Cash* measure, as defined in Appendix C and Section 3.2. Control variables are included following Equation 4, as defined in Section 4.1. In colums (4) to (6), the dependent variable is the natural logarithm of *LC Cost*, measured as the overall spread paid on newly opened lines of credit. Section 3.2 presents a detailed definition of LC Cost. Control variables are included following Equation 5, as defined in Section 4.2. Customer-base concentration is defined following Patatoukas (2012). Definitions of customer risk variables are reported in Appendices A and B. Definitions of all control variables are reported in Appendix C. Standard errors are corrected for heteroskedasticity and clustering at the supplier firm level (robust t-statistics are reported between brackets). *, **, and *** denote significance at the 10%, 5%, and 1%level, respectively.

| | Dependent variable = LC-to-Cash | | | Dependent variable = Ln(LC Cost) | | |
|---|---|---|---|---|---|---|
| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
| Customer Risk - Merton | -0.672*** | | | 0.510 | | |
| | (-3.188) | | | (0.902) | | |
| Customer Risk - CHS | | -0.688*** | | | 0.826* | |
| | | (-2.597) | | | (1.883) | |
| Customer Risk - First PC | | | -0.024*** | | | 0.028** |
| | | | (-3.761) | | | (2.227) |
| Customer Conc. | -0.050 | -0.065 | -0.023 | 0.317* | 0.303* | 0.101 |
| | (-0.792) | (-1.095) | (-0.359) | (1.829) | (1.822) | (0.697) |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6,756 | 7,149 | 6,150 | 1,801 | 1,900 | 1,618 |
| R-squared | 0.295 | 0.299 | 0.302 | 0.634 | 0.630 | 0.650 |
| Ind. dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes |