What Drives Corporate Trade Credit? The Roles of Financial Distress and Segment Information

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Abstract

This thesis examines the roles of financial distress and segment information disclosure in driving corporate trade credit. Using market-based and accounting-based measures of financial distress, the first empirical study examines whether financially distressed firms rely on trade credit as a source of financing. Using a sample of U.S. public firms throughout 1976-2017, we find that firms increase their use of trade credit when they are in financial distress. This is consistent with the view that suppliers offer trade credit to their distressed customers because they have a better ability to assess their customers' creditworthiness, and monitor and enforce debt repayment in the case of default than traditional financial institutions. The positive relation between financial distress and trade credit is magnified in firms with more information opacity and located in low-trust regions. However, further analyses show that financially distressed firms cannot always rely on trade credit. Overall, our results shed light on how, and when, financially distressed firms rely on trade credit as a source of financing.

Using the adoption of SFAS 131 as a quasi-natural experiment, the second empirical study investigates the impact of segment information disclosure on the use of trade credit. We find that firms that improved their segment disclosure by revealing new information about their segments upon adoption of SFAS 131 decrease their use of trade credit after the adoption of SFAS 131. This is in line with the theoretical prediction that the use of trade credit increases (decreases) when information asymmetry between firms and their capital providers is high (low). Consistent with the improvement in the firm's information environment, such an impact is greater for treatment firms with high default risk, a more opaque information environment, weak governance, and non-Big 4 auditors before SFAS 131. Having access to more sources of financing after the adoption of SFAS 131, these firms rely less on trade credit financing. Further analysis shows that the adoption of SFAS 131 reduces the firm's financial constraints and stock illiquidity, and increases the firm's issuance of equity.

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List of Abbreviations

2SLS	Two-Stage least squares
AICPA	American Institute of Certified Public Accountants
AIMR	Association for Investment and Management Research
AMEX	American Stock Exchange
AUD	Australian Dollar
CAD	Canadian Dollar
CHF	Swiss Franc
CPI	Consumer Price Index
CRSP	Center for Research in Security Prices
DD	Distance to Default
DiD	Difference-in-Differences
DiDiD	Difference-in-Difference-in-Differences
EDGAR	Electronic Data Gathering, Analysis, and Retrieval
FASB	Financial Accounting Standards Board
GBP	Great British Pounds
IBES	Institutional Brokers Estimate System
IFRS	International Financial Reporting Standards
IMF	International Monetary Fund
IV	Instrumental variables
JPY	Japanese yen
MDA	Multiple Discriminant Analysis
NASDAQ	National Association of Securities Dealers Automated Quotations
NCAR	National Center for Atmospheric Research
NPV	Net Present Value
NSSBF	National Survey of Small Business Finances
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
PSM	Propensity Score Matching
S&P 500	Standard and Poor's 500
SEC	Securities and Exchange Commission
SEK	Swedish Krona
SFAS	Statement of Financial Accounting Standards
SHELDUS	Spatial Hazard Events and Losses Database for the United States
SIC	Standard Industrial Classification
U.S.	United States
VIF	Variance Inflation Factors
WRDS	Wharton Research Data Services

Chapter 1 Introduction

1.1 Background and Motivation

The factors which drive firms' financing decisions is of considerable importance in the corporate finance literature. The issue of financing choice amongst equity, public debt, and bank financing has been widely debated since Modigliani and Miller (1958, 1963) published their seminal works. They question whether the choice between debt and equity is relevant to a firm's value. A large body of the literature considers different determinants, such as information asymmetry and agency problems, behind a firm's optimal choice of capital structure (e.g., Leland and Pyle, 1977; Myers, 1977; Campbell and Kracaw, 1980; Diamond, 1984; Myers and Majluf, 1984; Rajan, 1992; Rajan and Zingales, 1995; Houston and James, 1996; Bolton and Freixas, 2000; Hovakimian et al., 2001; Park, 2000; Frank and Goyal, 2003; Faulkender and Petersen, 2006; Antoniou et al., 2008 and many others). However, while these papers focus on firms' choices between public debt, bank loans, and equity, one specific important aspect, trade credit as a short-term source of financing, has received much less coverage in the literature (e.g., Meltzer, 1960; Schwartz, 1974; Petersen and Rajan, 1997; Ng et al., 1999; Wilner, 2000; Burkart and Ellingsen, 2004; Cuñat, 2007; Love et al., 2007; Fabbri and Menichini, 2010; Garcia-Appendini and Montoriol-Garriga, 2013; Fabbri and Klapper, 2016; Abdulla et al., 2017; Shang, 2020).

"Trade credit is created whenever a supplier offers terms that allow the buyer to delay payment" (Ng et al., 1999, p.1109). Trade credit, or accounts payable, is the single largest external source of short-term financing, as its aggregate volume exceeds the amount of other short-term sources of financing for firms in the United States (Petersen and Rajan, 1997).[1] In the United States, the accounts payable of non-financial corporate businesses accounted for approximately 2.4 trillion U.S. dollars in 2018.[2,3] Extensive empirical literature quantifies the amount of trade credit used by U.S. firms over the last four decades. For example, in 1988-1989, Petersen and Rajan (1997) find that the accounts payable is 4.4%, and 11.6%, of the total sales for small and large firms, respectively. A later study by Abdulla et al. (2017) finds that, during the period 1995-

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[1] Barrot (2016) argues that "accounts payable are three times as large as bank loans and fifteen times as large as commercial paper on the aggregate balance sheet of nonfinancial U.S. businesses" (p1975).
[2] This amount is 6% of total assets for non-financial corporate businesses.
[3] This figure is based on the Federal Reserve Flow of Funds in 2018 (Board of Governors of the Federal Reserve System).

2012, accounts payable is 9%, and 16%, of total assets for U.S. public and private firms, respectively. In our sample, the mean ratio of accounts payable to total assets is about 9.5% for U.S. public firms over the period 1976-2017, consistent with prior findings.

Despite the importance of trade credit as a short-term source of financing, the use of trade credit is relatively more expensive than other short-term sources of financing. According to Ng et al. (1999), suppliers do not charge their customers directly; instead, they offer a cash discount for early payment. For example, suppliers may offer trade credit with terms of '2/10 net 30'. These terms mean that trade credit is offered with a discount of 2% if the payment is made within 10 days after the invoice date. Otherwise, the full payment is due within 30 days after the invoice date. The 2% discount for 10 days is regarded as the implicit interest rate for trade credit if the full payment is made after 10 days. The value of annual implicit interest rate is about 43.9%. This is an extremely high rate compared with the rate of bank credit for a similar type of credit (Ng et al., 1999; Wilner, 2000; Cuñat, 2007).[4]

Nevertheless, there is an abundance of theoretical literature that justifies the existence of trade credit. On the one hand, for the borrowing firm, trade credit acts as a substitute for other sources of financing, i.e., firms use more trade credit when they face difficulties in accessing alternative sources of financing (e.g., Schwartz, 1974; Petersen and Rajan, 1997; Nilsen, 2002; Fisman and Love, 2003; Huang et al., 2011). On the other hand, suppliers are willing to provide trade credit to their customers who have limited access to other sources of financing, because they have financing advantages over conventional financial institutions. For example, through their frequent interactions with their customers, suppliers have a better ability to acquire information about customers' default risk (e.g., Smith, 1987; Mian and Smith, 1992; Biais and Gollier, 1997; Jain, 2001; Burkart and Ellingsen, 2004), liquidating their customer in the case of default (e.g., Mian and Smith, 1992; Frank and Maksimovic, 2005; Fabbri and Menichini, 2010), and enforcing debt payments by threatening to cut off the supply of products (Petersen and Rajan, 1997; McMillan and Woodruff, 1999; Cuñat, 2007).

In addition to the above-mentioned theoretical arguments, there are several other motives for the use of trade credit. For example, suppliers may provide trade credit to their customers to discriminate between risky and non-risky customers when

[4] According to Ng et al.(1999) the combination of a 2% discount for payment within 10 days and a net period ending on day 30 defines an implicit interest rate of 43.9%, which is computed as:
$Implicit\ rate = \{\left(\frac{100}{100-discount\%}\right)^{360/(number\ of\ days\ net-number\ of\ days\ discount)} - 1\}.$

discrimination directly through prices is legally prohibited (Petersen and Rajan, 1997). Suppliers are likely to offer highly priced trade credit, which is attractive only to risky customers, for whom access to the credit market is limited (Brennan et al., 1988). Furthermore, suppliers are likely to provide trade credit to their customers when they have an implicit equity stake in their customers' long-term survival (e.g., Wilner, 2000; Cuñat, 2007). Moreover, for the borrowing firm, trade credit can be used as a way to reduce the transaction costs of paying invoices by cumulating payments monthly or quarterly (Ferris, 1981). In a similar vein, suppliers may offer trade credit to their customers as a way to reduce the transaction costs of warehousing the inventory (Emery, 1987) or as a product warranty and verification (e.g., Lee and Stowe, 1993 and Long et al., 1993).

Given the importance of the use of trade credit as a source of short-term financing, many empirical studies have focused on the connection between the use of trade credit and various aspects related to the ability of the firm to access the credit and equity markets, such as firm-bank relations (Petersen and Rajan, 1997), liquidity shocks (e.g., Nilsen, 2002; Love et al., 2007; Garcia-Appendini and Montoriol-Garriga, 2013), financial distress (Molina and Preve, 2012; Garcia-Appendini and Montoriol-Garriga, 2020), stock market listing and stock liquidity (Abdulla et al., 2017; Shang, 2020) and information asymmetry (e.g., Chen et al., 2017; Chemmanur and Toscano, 2019; Li et al., 2021). Despite a significant number of studies conducted on the use of trade credit, the debate on what drives trade credit financing is still ongoing.

This thesis provides more insight into the drivers of the use of trade credit financing by addressing two important questions. In particular, the thesis investigates two interrelated questions, namely, (1) Can financially distressed firms rely on trade credit? (2) Does segment information disclosure, as an important input of credit risk assessment, affect the use of trade credit?

The first empirical chapter (Chapter 2) provides robust evidence that financial distress has statistically and economically significant impacts on the use of trade credit. Although previous studies by Molina and Preve (2012) and Garcia-Appendini and Montoriol-Garriga (2020) have provided evidence of the relationship between financial distress and the use of trade credit, their evidence leaves the relationship between financial distress and the use of trade credit subject to some doubt. For example, using the interest coverage ratio measure of financial distress, Molina and Preve (2012) find a positive relationship between financial distress and the use of trade credit. However, Garcia-Appendini and Montoriol-Garriga (2020) use a sample of bankrupt firms and find a drop in the use of trade credit as firms approach a default event. Garcia-Appendini and Montoriol-Garriga (2020) believe that the finding of Molina and Preve (2012) is limited to the initial stages of financial distress, and that it does not stand closer to bankruptcy. We believe that the relationship between trade credit and financial distress may be more nuanced if we investigate the issue using more sophisticated market-based and accounting-based measures of financial distress. Our work is partly motivated by a growing literature documenting significant differences in the accuracy of predicting financial distress among market-based and accounting-based models (e.g., Mensah, 1984; Hillegeist et al., 2004; Agarwal and Taffler, 2008).

In addition to examining the relationship between financial distress, using diverse measures of financial distress, we pay particular attention to a concern that the relationship between financial distress and the use of trade credit can be endogenous. Prior studies (e.g., Bris et al., 2005; Stromberg, 2000; Thorburn, 2000) show that firm characteristics have significant effects on firms getting into distress/bankruptcy and their choices of bankruptcy outlets. Moreover, it is possible that reverse causality between financial distress and the use of trade credit drive our results; it may be that increases in the use of trade credit lead to a rise in the level of financial distress. Previous research indicates a significant increase in financial distress when the firm significantly increases its use of trade credit as a source of financing (e.g., Altman, 1984; Opler and Titman, 1994; Andrade and Kaplan, 1998). Since the use of trade credit is an expensive source of financing (Ng et al., 1999; Wilner, 2000), it is expected that the use of trade credit prompts the level of financial distress. However, the issue of endogeneity has not been addressed in prior literature. Thus, in the first empirical chapter, we attempt to tackle the endogeneity issues and explore the casual link between financial distress and the use of trade credit.

In the second empirical chapter (Chapter 3), we proceed to investigate the effect of segment information disclosure on the use of trade credit. The study is motivated by the fact that segment information disclosure has been shown to be an important source of information for market participants interested in assessing the firm’s financial distress risk (Franco et al., 2016). The disclosure of more disaggregated segments can facilitate capital market participants' understanding of the extent to which the firm is industrially diversified so that each individual segment’s performance can be evaluated more thoroughly. Such disclosures can reduce the firm's information asymmetry concerning its diversification's actual co-insurance effect, allowing capital market participants to estimate and monitor its credit risk more easily (Franco et al., 2016). The earlier theoretical work of Lewellen (1971) and Higgins and Schall (1975) highlight that industrial diversification provides a co-insurance effect that decreases the firm's default risk. When diversified firms aggregate different industrial segments with imperfectly correlated earnings, they can benefit from a co-insurance effect that reduces the variability of its overall earnings (Lewellen, 1971; Galai and Masulis, 1976) and helps avoid countercyclical dead-weight costs (Hann et al., 2013).

A growing literature documents that segment information disclosure matters for the firm's information environment, including analysts' forecast accuracy (Venkataraman, 2001; Berger and Hann, 2003), stock price informativeness (Ettredge et al., 2005; Jayaraman and Wu, 2019), and cost of capital (Franco et al., 2016). This literature shows that segment information disclosure reduces information asymmetry and improves the firm's information environment. We contribute to the literature by examining the causal impact of segment information disclosure on the use of trade credit.

1.2 Overview of Empirical Studies and Contributions

In the first empirical study, we utilise Merton's (1974) distance-to-default as a market-based measure and Altman's (1968) Z score as an accounting-based measure of financial distress to investigate whether financially distressed firms use more trade credit as a source of financing. Using data on U.S. public firms for the period 1976-2017, we find that both measures of financial distress have a significant positive influence on the use of trade credit. The results are robust to alternative measures of trade credit, alternative measures of financial distress (i.e., the Ohlson (1980) model and the Campbell et al. (2008) model), and alternative model specifications. We further establish a causal relationship between financial distress and the use of trade credit using a range of identification methodologies. First, we employ propensity score matching techniques to account for the observable differences between distressed and non-distressed firms. Second, we employ a high-dimensional fixed effects model with the interacted industry-year and state-year fixed effects to control for unobservable time-varying industry-specific and state-specific heterogeneity. Third, we use a novel instrumentation strategy proposed by Alfaro et al. (2019) to address endogeneity in measuring financial distress by exploiting differential firm exposure to exchange rate, policy, and treasury volatility. Fourth, we utilise the 2007-2008 financial crisis as an exogenous shock to financial distress and study the impact of this shock on the use of trade credit. Last but not least, we use hurricane strikes as an exogenous shock to financial distress, relying on a triple differences (DiDiD) setup to study the causal effect of financial distress on the use of trade credit. Overall, our study suggests that financial distress does drive the use of trade credit.

Our findings are consistent with the following view: firms which enter financial distress face difficulties in accessing sources of financing, as the fear of default prevents capital providers from extending additional financing (Molina and Preve, 2012). Suppliers, on the other hand, have the incentive to extend trade credit to their financially distressed customers because of their comparative advantages over conventional lenders in investigating the creditworthiness of their customers and their superior ability to monitor and force repayment of the credit in the case of default (Petersen and Rajan, 1997). In addition, suppliers may be willing to help their distressed customers especially if the expected level of financial distress is not extremely high and they find it profitable to provide a subsidy for distressed customers in the form of highly priced trade credit (Brennan et al., 1988; Petersen and Rajan, 1997). Our cross-sectional analyses support these arguments and show that the positive impact of financial distress on the use of trade credit is greater when firms have high information opacity or are located in regions characterised by low social trust. Overall, the cross-sectional analyses of this chapter provide strong and new evidence supporting some of the theories of trade credit mentioned above in a case where the firm is financially distressed. These results support the view that suppliers have financing advantages over conventional financial institutions, which places them in a better position to work as liquidity providers to their financially distressed customers. Traditional financial institutions might be concerned about the default risk of financially distressed firms, especially if these firms have a more opaque information environment or locate in low social trust regions. On the other hand, the financing advantages of suppliers help them overcome asymmetric information and moral hazard problems if their distressed customers are in default.

However, we find that financially distressed firms cannot always rely on trade credit. We show that when distressed customers become particularly risky and may affect suppliers' value negatively, suppliers are less willing to offer trade credit to such customers. In particular, we find that when distressed firms are major customers, they receive less trade credit relative to non-distressed major customers. One possible explanation for this finding is that, since suppliers are highly dependent on their major customers, to keep helping these customers when they are in financial distress may put suppliers at risk of default (e.g., Hertzel et al., 2008; Kolay et al., 2016). Moreover, given that suppliers are likely to lose confidence in their distressed customers, it is expected that distressed firms are only able to use trade credit when the level of financial distress is not very high. In support of this view, we find that the use of trade credit increases when the firm faces financial distress and decreases quadratically with the level of financial distress, indicating that financial distress exhibits an inverted-U pattern with the use of trade credit. In a nutshell, our results imply that trade credit can be used as a source of financing by financially distressed firms facing difficulties accessing sources of financing. However, these firms cannot always rely on trade credit if their level of financial distress is very high or their financial distress affects their suppliers' value negatively. Thus, the results provide new insights on how and when financially distressed firms rely on trade credit as a source of financing.

The first empirical study contributes to the literature in a number of ways. First, this study extends the work of Molina and Preve (2012) and Garcia-Appendini and Montoriol-Garriga (2020) by utilising different measures of financial distress, market-based and accounting-based measures, to join the debate concerning the use of trade credit in the case of financial distress. Our results complement Molina and Preve (2012) by showing that financial distress in the early stages can lead to an increase in the use of trade credit, and also support the finding of Garcia-Appendini and Montoriol-Garriga (2020) by highlighting that financially distressed firms cannot rely on trade credit when the level of financial distress is extremely high. Second, our study contributes to the literature by establishing a causal link between financial distress and the use of trade credit. To the best of our knowledge, this is the first study that considers the endogenous association between financial distress and the use of trade credit and explicitly address the endogeneity issues. Finally, our study provides new insights concerning the claim that suppliers help their distressed customers because they have business relations with their customers (Wilner, 2000; Cuñat, 2007). While the existing literature shows that suppliers are likely to provide liquidity to their distressed customers because they have an implicit equity stake in their customers' business, we show that suppliers extend trade credit to their major customers only when they are not in financial distress. This finding is related to the existing literature investigating the effect of financial distress along the supply chain. To the extent that supplier firms' value can be negatively affected by their major customers' bankruptcy filings (Hertzel et al., 2008; Jorion and Zhang, 2009), it is not surprising, as documented in our study, that suppliers are likely to stop extending trade credit to major customers which are financially distressed.

Having established a positive effect of financial distress on the use of trade credit, we now turn to explore how a specific source of information, that is important to capital market participants in firms' credit risk assessments, drives the use of trade credit. More specifically, the second empirical study in this thesis examines the effect of an exogenous change in the firm's information environment on a firm's use of trade credit, using the change in U.S. segment reporting rules from SFAS 14 to SFAS 131, in 1998/1999, as a quasi-natural experiment. The adoption of the Statement of Financial Accounting Standards No. 131 (SFAS 131) prompts firms to reveal new information about their corporate diversification status, which helps the capital market participants assess the firm's financial distress risk more accurately. As a consequence of revealing this new information about the firm's corporate diversification status, firms are expected to get better access to finance, which allows the firms to rely less on trade credit financing.

We use a difference-in-differences (DiD) research design to compare the effect of SFAS 131 on the use of trade credit, over the period 1994-2002, among firms that disclosed a single segment before the adoption of SFAS 131 and were forced to reveal their previously hidden diversification status upon the adoption of SFAS 131 (treatment group) and firms that disclosed a single segment before and after the adoption of SFAS 131 (control group). We find that firms that improved their segment disclosure, by revealing new information about their segments upon adoption of SFAS 131, significantly decreased their use of trade credit after the adoption of SFAS 131. We confirm the robustness of our results by using an alternative control group, which helps to control for the randomness of firms' assignment to the control group. We also employ a propensity score-matched (PSM) sample based on ex-ante firm characteristics to correct for any possible differential trends among treatment and control firms. We further include industry-year fixed effects and state-year fixed effects to control for unobservable time-variant industry-specific and state-specific heterogeneity. The results survive these tests and, in addition, are robust to different estimation windows and alternative measures of trade credit.

Our findings are consistent with the theoretical literature on trade credit (e.g., Smith, 1987; Brennan et al., 1988; Biais and Gollier, 1997) that information asymmetry drives the use of trade credit. Since suppliers have an informational advantage over traditional financial institutions, firms are likely to resort more to supplier's trade credit as a source of financing when the extent of information asymmetry facing capital providers about firms increases. However, when new information, such as firms' diversification's actual co-insurance effect, is revealed to the market, capital providers may be more willing to extend additional financing because the segment information makes it easier and less costly estimate and monitor the firm's credit risk. Thus, the adoption of SFAS 131 is likely to be beneficial for firms that suffered problems in accessing sources of financing before the adoption of SFAS 131. For example, suppose financially distressed firms face difficulties in accessing financing sources because the fear of default prevents capital providers from extending financing. In this case, the adoption of SFAS 131 is beneficial for these firms because it reduces the capital providers' information asymmetry about their true underlying diversification, whose co-insurance effect has been documented to reduce default risk (Lewellen, 1971). Consistent with these arguments, our cross-sectional analysis shows that the impact of SFAS 131 on the use of trade credit is greater among treatment firms with high default risk, a more opaque information environment, weak governance, and with non-Big 4 auditors before the adoption of SFAS 131. Overall, our cross-sectional analyses of this chapter highlight some cases where firms that suffer problems of information asymmetry will be more affected by the mandatory adoption of segment disclosure by relying less on trade credit financing after the adoption of SFAS 131. These results support the argument that information asymmetry is a crucial determinant of the use of trade credit.

Furthermore, in line with our expectation that the reduction in the information asymmetry between firms and their capital providers improves the firm's access to sources of financing, our further analysis documents that the adoption of SFAS 131 reduces the firm's financial constraints and stock illiquidity and increases the firm's issuance of equity. These additional results support the argument that information asymmetry drives the firm's financing choices. In particular, the adoption of SFAS 131 could lead the firms to substitute trade credit financing with other external financing (e.g., equity) that are informationally sensitive.

The second empirical study contributes to the literature in two important ways. First, this study adds to the literature documenting the effect of credit and equity market accessibility on the use of trade credit (e.g., Petersen and Rajan, 1997; Giannetti et al., 2011; Nilsen, 2002; Love et al., 2007; Garcia-Appendini and Montoriol-Garriga, 2013;

Abdulla et al., 2017; Chemmanur and Toscano, 2019; Chen et al., 2017; Shang, 2020; Li et al., 2021). In this study, we provide new evidence on how exogenous changes in the information environment affect a firm's use of trade credit. While existing studies establish a causal relationship between the use of trade credit and different information sources, such as analyst coverage and financial reporting (e.g., Chemmanur and Toscano, 2019; Chen et al., 2017; Li et al., 2021), to the best of our knowledge, this study is the first to examine the impact of segment information disclosure on the use of trade credit financing and to document that firms that have revealed new information about their corporate diversification status, under SFAS 131, rely less on trade credit financing. Second, this study contributes to the literature on the economic consequences of the mandatory adoption of SFAS 131 (e.g., Herrmann and Thomas, 2000; Berger and Hann, 2003; Cho, 2015; Jayaraman and Wu, 2019; Franco et al., 2016) by documenting that the adoption of SFAS 131 has a significant impact on the use of trade credit as a short-term source of financing.

1.3 Thesis Structure

This thesis includes four chapters. The remainder of the thesis is organised as follows. Chapter 2 investigates whether financially distressed firms rely on trade credit. Chapter 3 examines the impact of segment information disclosure, using the adoption of SFAS 131 as a quasi-natural experiment, on the use of trade credit. Chapters 2 and 3 have their own introduction, literature review and hypothesis development, data and sample selection, research design, empirical results and conclusion. Chapter 4 concludes the thesis, draws implications and identifies areas for future research.

Chapter 2 Can Financially Distressed Firms Rely on Trade Credit?

Abstract

This chapter investigates whether financially distressed firms use trade credit as a source of financing for a large sample of U.S. public firms between 1976 and 2017. Using market-based and accounting-based measures of financial distress, we provide evidence that firms increase their use of trade credit as a source of financing when they are in financial distress. These results continue to hold when we use alternative measures of trade credit, alternative financial distress measures, alternative model specifications, and sub-period analysis. Further, we establish the causality of financial distress on trade credit using different identification strategies, such as propensity score matching, a high-dimensional fixed-effects model, two-stage least squares estimation, and a difference-in-differences approach. The results are consistent with the view that suppliers offer trade credit to their financially distressed customers because they have a better ability to assess their customers' creditworthiness, and monitor and enforce debt repayment in the case of default than traditional financial institutions. Our cross-sectional analysis reveals that the positive impact of financial distress on the use of trade credit is more pronounced among firms with more information opacity and firms located in low social trust regions. However, further analyses show that financially distressed firms cannot always rely on trade credit. In particular, we find that financially distressed firms receive less trade credit when they are major customers. Also, we find an inverted U-shaped relation between financial distress and the use of trade credit. Overall, our results shed light on how and when financially distressed firms rely on trade credit as a source of financing.

2.1 Introduction

The risk of a firm's financial distress is a matter of major concern to the shareholders and creditors of a firm. When a firm faces financial distress, its ability to raise additional financing is severely restricted (Gertner and Scharfstein, 1991), as the fear of default makes capital market participants reluctant to extend additional financing. In this context, trade credit, the source of financing provided by suppliers, can substitute for traditional sources of financing when the latter is limited (Meltzer, 1960; Petersen and Rajan, 1997; Love et al., 2007). Previous research (e.g., Evans and Koch, 2007; Jorion and Zhang, 2009) shows that most industrial firms that are exposed to bankruptcy events use more trade credit as a source of financing. Trade credit is likely to help such firms to successfully avoid Chapter 11 of the U.S. Bankruptcy Code, leading to a higher rate of survival. This rationale has been explained by the theoretical models of trade credit (Petersen and Rajan, 1997; Wilner, 2000; Cuñat, 2007) that argue that when suppliers have an implicit equity stake in their customers' business, they are likely to provide trade credit to their customers facing financial distress in order to save valuable customer relations and maintain continued business. However, such an argument is hard to reconcile with the assumption that suppliers lack contractual seniority (Garvin, 1996), which puts them at considerable risk in the case of customer bankruptcy. Consistent with this view, some early studies, such as Baxter (1967), Altman (1984), Titman (1984), and Andrade and Kaplan (1998), argue that financially distressed firms are expected to face problems with their suppliers. These studies argue that suppliers may be less willing to supply their products to financially distressed firms, which indicates that financially distressed firms could face difficulties obtaining trade credit.

Nevertheless, empirical studies by Molina and Preve (2012) and Garcia-Appendini and Montoriol-Garriga (2020) have quantified the impact of financial distress on the use of trade credit. In particular, using interest coverage ratio a measure of financial distress, Molina and Preve (2012) find that financially distressed firms use a significantly larger amount of trade credit to substitute for other sources of financing. However, Garcia-Appendini and Montoriol-Garriga (2020) find that the increase in the use of trade credit by distressed firms is limited to the initial stages of financial distress, but it is unlikely to hold when a default is imminent. More specifically, Garcia-Appendini and Montoriol-Garriga (2020) use a sample of firms that eventually filed for bankruptcy and document a decrease in the use of trade credit as firms approach bankruptcy compared to a control sample of non-bankrupt firms. However, while these studies have increased our understanding of the impact of financial distress on the use of trade credit, the results of Molina and Preve (2012) and Garcia-Appendini and Montoriol-Garriga (2020) cast some doubt on whether financially distressed firms use more, or less, trade credit as a source of financing. Given the seemingly contradicting evidence from the two prior studies, this study aims to join the debate about whether financially distressed firms use more trade credit financing by using more sophisticated measures of financial distress. More specifically, this study uses market-based and accounting-based measures of financial distress to examine the impact of financial distress on the use of trade credit.

Our study is motivated by several studies that cast doubt on the validity of accounting-based models in predicting financial distress versus market-based models. Prior studies on financial distress (e.g., Mensah, 1984; Begley et al., 1996; Hillegeist et al., 2004; Agarwal and Taffler, 2008) argue that accounting-based measures of financial distress may not reflect all the publicly available information about the probability of default. In particular, Mensah (1984) suggests that the distribution of accounting ratios used in accounting-based models changes over time and, thus, they need to be redeveloped periodically. Agarwal and Taffler (2008) show that accounting-based models present past performance and may not be informative in predicting the future of a firm. Further, they show that the financial statements used in predicting these models are subject to manipulation by management. Accounting-based models are also prepared under the going-concern principle, which assumes that firms will not go bankrupt (Hillegeist et al., 2004). On the other hand, market-based measures of financial distress provide significantly more information about the probability of default than the accounting-based measures (Hillegeist et al., 2004). In addition, market-based models are unlikely to be affected by accounting policies, and they are likely to reflect future expected cash flows (Agarwal and Taffler, 2008). For these reasons, market-based models of financial distress are likely to outperform accounting-based models. Therefore, we can yield more precise estimates of the relationship between financial distress and the use of trade credit if we examine this relationship using market-based and accounting-based measures of financial distress.

In addition, prior studies that investigate the impact of financial distress on the use of trade credit may ignore that financial distress is endogenously related to the use of trade credit. For example, increasing the use of trade credit increases financial distress, while an increase in financial distress should cause an increase in the use of trade credit. To the best of our knowledge, however, no research has addressed the issue of endogeneity between financial distress and the use of trade credit. Establishing a causal link between financial distress and the use of trade credit is challenging because it requires an exogenous shock to financial distress. Thus, another objective of this study is to establish a causal relationship between financial distress and the use of trade credit, using different identification methodologies. We employ a range of approaches to deal with endogeneity issue intrinsic to the financial distress- trade credit relation.

We rely on several motives for trade credit usage to develop our testable hypotheses. First, firms facing financial distress are expected to have limited access to sources of financing because their capital providers may be less willing to extend additional financing to avoid the risk of default (Molina and Preve, 2012). On the other hand, suppliers may be more willing to help their financially distressed customers by offering trade credit because they have comparative advantages over financial institutions in acquiring information, assessing the creditworthiness of customers, and enforcing debt repayment. Theoretical models by Smith (1987) and Biais and Gollier (1997) show that suppliers are likely to have informational advantages over traditional financial institutions in identifying prospective defaults of their customers, which facilitates the sorting of low from high default risk. Thus, if this informational advantage helps suppliers assess their customers' default risk, they are expected to extend trade credit to their customers facing temporary financial distress. Other theoretical arguments (e.g., Petersen and Rajan, 1997; McMillan et al., 1999; Cuñat, 2007) suggest that under the assumption of low competition in the product market, suppliers may offer trade credit to their financially distressed customers because they have stronger market power than traditional financial institutions to enforce debt repayment in the case of customer default. Alternatively, suppliers are likely to have a liquidation advantage over traditional financial institutions, which places suppliers in a better position to work as liquidity providers to their financially distressed customers. This liquidation advantage enables suppliers to reclaim goods sold to distressed customers in the case of default (Petersen and Rajan, 1997; Frank and Maksimovic, 2005; Fabbri and Menichini, 2010).

Second, suppliers may help their financially distressed customers, even if they do not have financing advantages over traditional financial institutions, because trade credit might be used for price discrimination. In particular, suppliers may have the incentive to benefit from their distressed customers in the short-run, such as offering highly-priced trade credit to increase their profit margin (Brennan et al., 1988, Petersen and

Rajan, 1997). Finally, suppliers may offer trade credit to their distressed customers to maintain a valuable business relationship with their customers in the long run (Wilner, 2000; Cuñat, 2007). This is especially important when suppliers have a large implicit equity stake in their distressed customers (Petersen and Rajan, 1997). Taken together, all these arguments suggest that suppliers are more willing to offer trade credit to their financially distressed customers facing difficulties in accessing sources of financing. Thus, we hypothesise a positive relationship between financial distress and the use of trade credit.

Financial distress may however decrease the use of trade credit if suppliers progressively lose confidence in their distressed customers (Smith, 1987; Garcia-Appendini and Montoriol-Garriga, 2020). This is especially so when firms have a high probability of default and bankruptcy laws limit the suppliers' ability to liquidate their customers in case of default (Garvin, 1996). Prior research shows that suppliers are likely to be less inclined to supply products to their distressed customers, and they may face difficulty obtaining trade credit from their suppliers (Baxter, 1967; Altman, 1984). Thus, suppliers, like other capital providers, might be concerned about the default risks of their distressed customers, and they are likely to be less willing to offer trade credit to these firms.

To test our prediction, we empirically examine the impact of financial distress on the use of trade credit using a large sample of U.S. public firms over the period 1976–2017. We employ two measures of financial distress that are widely used in the literature, namely, the Merton (1974) distance-to-default model (DD), which is based on market data, and the Altman (1968) Z-score, which is based on accounting data. Both measures of financial distress document a significant positive association between financial distress and the use of trade credit measured as the accounts payable to total assets ratio. This effect is both statistically significant and economically sizeable across all model specifications; a one-standard-deviation increase in our two measures of financial distress results in a 0.13 to 0.63 percentage points increase in the accounts payable ratio. Taken together, we find consistent evidence supporting our main hypothesis that financially distressed firms use more trade credit as a source of financing.

This finding is robust to alternative measures of trade credit, alternative measures of financial distress, using principal component analysis to combine the individual financial distress measures into an aggregate measure, alternative model specifications, as well as to alternative sample periods. In particular, our results do not change when we use ratios of accounts payable to costs of goods sold, or accounts payable to total sales measures of the use of trade credit. Further, our results hold if we use the Ohlson (1980) model or the Campbell et al. (2008) model measures of financial distress. In addition, our results do not change when we use principal component analysis to construct a comprehensive financial distress measure based on Merton (1974), Altman (1968), Ohlson (1980), and Campbell et al. (2008) models. Also, our results remain similar when we re-estimate our baseline model using both Fama and MacBeth's (1973) regressions and Petersen's (2009) two-way clustering. Finally, our results show that a positive relationship between financial distress and the use of trade credit is robust and not driven by any specific sample period.

Overall, our baseline results offer a good starting point, that financially distressed firms increase their use of trade credit. However, an important concern with our baseline regression model is that the relation between financial distress and the use of trade credit may tell us little about causality, because of reverse causality and omitted variable concerns. It is expected that financial distress measures are not exogenous and, thus, the impact of financial distress on the use of trade credit could happen either because the same firm characteristics omitted from our analysis simultaneously drive both the financial distress and the use of trade credit, or because higher use of trade credit brings about an increase in financial distress. To address these concerns and explore the causality of the relationship between financial distress and the use of trade credit, we employ several tests.

First, we conduct a propensity score matching (PSM) analysis, whereby distressed firm-years are matched with otherwise indistinguishable non-distressed firm-years. This approach helps reduce the effects of observable firm characteristics that are difficult to fully control in the regressions and confirm the impact of financial distress on the use of trade credit. We continue to observe a positive and significant effect of financial distress on the use of trade credit.

Second, we adopt a high-dimensional fixed-effects model to control for unobservable firm characteristics. More specifically, in addition to regressions with firm fixed effects, we use a specification with state-year and industry-year fixed effects to mitigate concerns about other time-varying industry or state level explanations. We again find our results remain qualitatively similar.

Third, we employ an instrumental variable approach to address the endogeneity concern. Following Alfaro et al. (2018), we use nine instruments for financial distress measures. In particular, we use nine different sources of uncertainty shocks: seven widely traded currencies, U.S.10-year treasuries and the policy uncertainty index. These instruments could have an exogenous effect on firm-level volatility, and they are likely to increase financial distress. Thus, these instruments satisfy the relevance condition of the instrumental variable approach. We once again find that the instrumented financial distress significantly increases the use of trade credit.

Fourth, we undertake a difference-in-differences approach using the 2007-2008 financial crisis as an exogenous shock leading to increased financial distress. In particular, we use firms that entered the financial crisis with a high level of leverage and low interest coverage as treatment firms to examine how, and whether, the increase in financial distress following the crisis affects the use of trade credit. These firms are likely to face more financial distress during the financial crisis, which makes it difficult for these firms to access sources of financing and, thus, they are likely to increase their use of trade credit. This test helps us alleviate the concern that reverse causality drives our results, because the crisis event is unlikely to have been caused by firms' use of trade credit. Again, we continue to observe that the empirical relation between financial distress and the use of trade credit appears to be causal.

Finally, we utilise the hurricane strikes that occurred in the U.S. over the period 1979-2011 as an exogenous shock to financial distress. These hurricane strikes caused severe economic and inland damage, which would increase firms' financial distress (Aretz et al., 2019). Following Aretz et al. (2019), we conduct a triple difference-in-differences (DiDiD) test that allows us to examine the effects of hurricane strikes on the use of trade credit through increasing financial distress, not through other non-distress reasons. More specifically, we first compare hurricane-struck firms with non-hurricane-struck firms. We then compare pre-hurricane-strike non-distressed firms with pre-hurricane-strike distressed firms. Our DiDiD results show that hurricane-struck firms with high ex-ante financial distress (i.e., those located in a hurricane-struck county and which faced higher financial distress one year before the hurricane strike) have significantly higher use of trade credit.

In summary, all of the above approaches and tests produce consistent evidence that increased financial distress positively affects the use of trade credit. Our results suggest that suppliers can work as liquidity providers to their customers when they are in financial distress. This finding can be explained by several of the motivations for the use of trade credit mentioned above. In order to further understand when suppliers are likely to help their financially distressed customers, we now present a battery of cross-section tests to reinforce the inference derived from the above baseline results. We examine two different cross-sectional analyses: information opacity and social trust.

We first hypothesise that the positive effect of financial distress on the use of trade credit is more pronounced when the underlying firms have a more opaque information environment. These firms may experience more difficulties in accessing sources of financing because capital providers are likely to face difficulties in obtaining sufficient information to monitor and assess the credit quality of these firms. Since suppliers have an information advantage over financial institutions in monitoring and sorting low- from high-default risk customers (Smith, 1987; Biais and Gollier, 1997), they are more likely to help their distressed customers that have more information opacity. Therefore, the positive relationship between financial distress and the use of trade credit is expected to be greater for firms with more information opacity. Consistent with our expectations, using the number of analysts following the firm and probability of informed trading (PIN) measures of information opacity, we find that the positive impact of financial distress on the use of trade credit is more pronounced for firms with a more opaque information environment.

The other cross-sectional analysis relates to the degree of social trust in the region of the distressed firm's headquarters. In particular, we predict that the impact of financial distress on the use of trade credit will be greater for firms headquartered in low social trust regions. The rationale behind this test relies on the idea that firms headquartered in high social trust regions are expected to report more reliable information about their credit risk. Also, these firms are perceived as trustworthy and honest by capital market participants (Guiso et al., 2004; Jha, 2019). Thus, these firms are likely to have better access to external financing, enabling them to rely less on trade credit financing. On the other hand, firms headquartered in low social trust regions are perceived as untrustworthy because they may misbehave or take actions that are likely to harm capital providers. Thus, these firms are expected to have difficulties in accessing sources of financing and rely heavily on trade credit when they are in financial distress. Accordingly, since suppliers have a financing advantage in assessing, monitoring and enforcing debt repayment over traditional financial institutions, they may be more willing to offer trade credit to distressed customers in low social trust regions. Consistent with this idea, using the county-level social trust index of Rupasingha et al.

(2006), we find that the positive impact of financial distress on the use of trade credit is greater for firms in low social trust regions.

Our findings so far suggest that when a firm enters financial distress, it uses more trade credit to substitute for alternative sources of financing. We attribute this finding to the fact that suppliers are more willing to help their financially distressed customers because they have a better ability to monitor and liquidate their customers in the case of default than traditional financial institutions. Moreover, suppliers may offer trade credit to their distressed customers because they expect the financial distress level to be not very high, and they may find it profitable to provide a subsidy for distressed customers in the form of highly-priced trade credit (Brennan et al., 1988; Petersen and Rajan, 1997). However, the question remains as to whether financially distressed firms always rely on trade credit financing and whether their suppliers always help. Suppliers may be less willing to offer trade credit to their financially distressed customers when they become particularly risky and affect suppliers' value negatively. As further evidence in support of this view, we examine two scenarios in which suppliers may be less willing to help their financially distressed customers.

First, given that suppliers are highly dependent on their customers, who account for a large proportion of their sales, continuing to help these customers when they are in financial distress may put suppliers under the risk of default. Prior studies (e.g., Hertzel et al., 2008; Kolay et al., 2016) show that that major customers' financial distress has a significant impact on their suppliers' stock returns. They find that there are significant negative abnormal stock returns for suppliers following bankruptcy announcements of their major customers. Since the information about major customers is publicly available, shareholders of the supplier firm may use this information to predict their suppliers' returns (Cohen and Frazzini, 2008; Alldredge and Cicero, 2015). Thus, if the supplier firm's shareholders recognise the negative news (i.e., becoming financially distressed or declaring bankruptcy) about its major customers, they are likely to adjust their valuation of the supplier firm, which, in turn, affects their valuation negatively. Accordingly, suppliers are expected to be less willing to help their distressed customers when they are major customers, due to the significant losses incurred if they keep helping these customers. To test this prediction, we use data from Compustat's Segment Customer files to identify firms that are major corporate customers. Consistent with our prediction, we find that the positive impact of financial distress on the use of trade credit is weaker for firms that are major customers. At the same time, we find that firms use less trade credit when they are not in financial distress, but this relationship is weaker when firms are major customers. These findings suggest that firms that are major customers tend to use less (more) trade credit financing when they are financially distressed (non-distressed)

Second, suppliers are likely to help their distressed customers as long as the level of financial distress is not extremely high, but this does not hold closer to the default event (Garcia-Appendini Montoriol-Garriga, 2020). Under the assumption that bankruptcy laws probably limit the suppliers’ ability to liquidate their default customers (Garvin, 1996), suppliers are expected to be less inclined to offer trade credit to their customers when they are close to a bankruptcy event. Moreover, since suppliers have an information advantage in the sorting of low- from high-default risk customers, they are likely to be able to exit early from a distressed relationship when the default risk is very high (Smith, 1987; Biais and Gollier, 1997). Thus, we expect firms to use more trade credit when they face financial distress, but they will use less trade credit when financial distress becomes very high. In other words, we expect that the relationship between financial distress and the use of trade credit is non-linear. To test this conjecture, we use a quadratic term for financial distress to capture a possible non-linear relationship between financial distress and the use of trade credit. Consistent with our prediction, we find that the use of trade credit increases when the firm faces financial distress and decreases quadratically with the level of financial distress, suggesting that there is an inverted-U pattern between financial distress and the use of trade credit.

This study contributes to the literature in the following ways. First, our study extends the work of Molina and Preve (2012) and Garcia-Appendini and Montoriol-Garriga (2020) by employing different measures of financial distress, namely, market-based and accounting-based models, to revive the debate about whether financially distressed firms rely on trade credit as a source of financing. We build on, and extend, the findings of Molina and Preve (2012) to show that both accounting and market-based measures infer a positive impact of financial distress on the use of trade credit. We further support the findings of Garcia-Appendini and Montoriol-Garriga (2020) to show that the use of trade credit declines quadratically with financial distress. Second, we complement the prior literature by establishing a causal link between an increase in financial distress and the use of trade credit by applying a series of identification strategies, such as an instrumental variable two-stage regression and a difference-in-differences approach, which relies on two quasi-natural experiments in which increased financial distress is caused by exogenous shocks. This study is the first to address the endogenous association between financial distress and the use of trade credit and provides more insights on how exogenous changes in financial distress affect corporate trade credit.

Finally, our study provides new empirical evidence on the impact of customer-supplier ties on the relationship between financial distress and the use of trade credit. Broadly, our results add to the literature that claims that suppliers help financially distressed customers because they have an implicit equity stake in their customers' business (Wilner, 2000; Cuñat, 2007). Using a sample of customer-supplier pairs, Garcia-Appendini and Montoriol-Garriga (2020) show that suppliers facing high switching costs maintain their business relationship with their financially distressed major customers and provide them with more trade credit. While studies find that financially distressed firms receive more trade credit when they are major customers, our results show that suppliers may be more willing to help their distressed customers when they are non-major customers relative to major customers. Our study suggests that suppliers are more likely to extend trade credit to their non-financially distressed major customers. Thus, our work extends this literature by documenting that suppliers may help their financially distressed customers for reasons unrelated to being major customers. This study is also related to existing work on how a concentrated customer base increases suppliers' risk (e.g., Jorion and Zhang, 2009; Hertzel et al., 2008; Hui et al., 2012), who shows that suppliers' value may be negatively affected by their financially distressed major customers; as a consequence, they extend less trade credit.

The remainder of the chapter proceeds as follows. Section 2.2 provides a review of the related literature and discusses the hypotheses development of our research. Sample collection procedure and variables, research design, and descriptive statistics are described in Section 2.3. Section 2.4 discusses our empirical results, while Section 2.5 concludes the study.

2.2 Related Literature and Hypothesis Development

This section provides a brief review of the existing empirical literature on trade credit, emphasizing those papers most relevant to our study, followed by a discussion of the development of our hypotheses, corresponding to the research questions outlined in our introduction.

2.2.1 Related Literature

Prior research on trade credit has sought to understand why firms should want to borrow from suppliers rather than from traditional financial institutions (See Schwartz, 1974; Mian and Smith, 1992; Long et al., 1993; Deloof and Jegers, 1996; Petersen and Rajan, 1997; Ng et al., 1999). The traditional explanation of trade credit usage is that it plays a number of non-financial roles. In particular, trade credit plays a role in reducing transaction costs (e.g., Ferris, 1981), it allows price discrimination between customers with different default risks (Brennan et al., 1988), it provides an implicit warranty guaranteeing product quality when customers cannot observe product quality (Long et al., 1993), and it even maintains long-term relations between suppliers and customers (Wilner, 2000; Cuñat, 2007).

Although these non-financial motivations can explain the existence of trade credit usage, they do not consider any prediction of how firms' access to sources of financing affects the use of trade credit. Arguments relating to the financing advantages of suppliers over other sources of financing from traditional financial institutions have attempted to fill this gap (Biais and Gollier, 1997; Burkart and Ellingsen, 2004). The financial motives argue that firms with limited access to traditional sources of financing resort to trade credit from their suppliers because the latter have financing advantages over traditional financial institutions (Schwartz and Whitcomb, 1979; Ferris, 1981; Emery, 1984; Mian and Smith, 1994; Jain, 2001). The literature shows that these financing advantages are available to suppliers because they have better information about their customers (Bias and Gollier, 1997), they can lower their borrower's opportunism (Burkart and Ellingsen, 2004), or a liquidation advantage (i.e., the advantage in salvaging value from existing assets) over traditional financial institutions (Petersen and Rajan, 1997; Fabbri and Menichini, 2010).

Suppliers have a comparative advantage over traditional financial institutions in acquiring information about buyers that helps them identify prospective defaults of their customers more quickly than if financial institutions are the sole providers of financing (Smith, 1987). Moreover, in the case of a customer default, suppliers might be able to extract a greater liquidation value from the inputs collateralized than financial institutions, as they can better repossess and resell goods to other customers (Mian and Smith, 1992; Frank and Maksimovic, 2005; Fabbri and Menichini, 2010). Further, suppliers may be able to threaten to cut off future intermediate goods in the event of customer default. This enforceability power of suppliers may be especially credible when the business link between suppliers and customers is costly to substitute (Petersen and Rajan, 1997; Cuñat, 2007).

These arguments suggest that when firms are unable to raise finance from traditional sources, suppliers are likely to be more willing to help these firms, due to their financing advantages over traditional financial institutions. In our study, the rationale behind the relationship between trade credit and financial distress is related to these financing advantages of suppliers. Moreover, it could be that some of the non-financial motivations of trade credit, such as long-term supplier-customer business relationships and price discrimination, are related to our study.

Empirically, several existing studies highlight the importance of the use of trade credit as an alternative source of financing for those firms for whom borrowing from specialised financial institutions is prohibitively costly (Banerjee et al., 2004). Those studies focus on various aspects of firms' access to credit or equity markets, such as their banking relationship (Petersen and Rajan, 1997), industry characteristics (Ng et al., 1999; Fisman and Love, 2003), stock market listing status (Abdulla et al., 2017), and stock liquidity (Shang, 2020). They generally find that firms facing more financial constraints, which typically have less access to credit or equity markets, use more trade credit.

While the studies listed above examine the relationship between various firm characteristics related to access to credit or equity markets and the use of trade credit, there is a strand of literature investigating the impact of macroeconomic shocks on the use of trade credit. Early work by Meltzer (1960) demonstrates the so-called "redistribution view" of trade credit. This view assumes that during "tight money" periods, bank credit is redistributed by trade credit through the suppliers with stronger liquidity levels to the customers with weaker financial conditions. Love et al. (2007) support this view by investigating the use of trade credit during a financial crisis. Specifically, this study focuses on the 1997 Asian financial crisis in six emerging economies (Malaysia, Mexico, Indonesia, Thailand, South Korea, and the Philippines) and finds that firms increase their use of trade credit during the crisis period. Garcia-Appendini and Montoriol-Garriga (2013) likewise provide evidence on this relation by focusing on the recent financial crisis (i.e., the 2007-2008 global financial crisis) and find that suppliers with higher pre-crisis liquidity positions extend more trade credit to their financially constrained customers during the crisis period, compared to suppliers with lower pre-crisis liquidity levels.

Overall, these studies reviewed above suggest that firms are likely to use more trade credit when access to traditional sources of financing is difficult. Similarly, the use of trade credit is crucial for firms facing financial distress. As documented by prior literature (Jorion and Zhang, 2009), the most exposures to bankruptcy of U.S. industrial firms tend to prefer trade credit from suppliers over financial institutions. Indeed, when firms face financial distress, their ability to access traditional sources of financing is severely curtailed, as the fear of default prevents capital providers from extending additional financing (Molina and Preve, 2012). On the other hand, suppliers are likely to extend trade credit financing or agree to debt forgiveness when firms file for bankruptcy, leading to a higher survival rate through the successful avoidance of Chapter 7 of the U.S. Bankruptcy Code (Evans and Koch, 2007).

Although prior studies make an important effort towards addressing the use of trade credit in the case of financial distress, the impact of financial distress on the use of trade credit remains open to debate. For example, using a sample of U.S. firms from Compustat over the period of 1978-2000, Molina and Preve (2012) examine the impact of financial distress, measured as the ratio of interest coverage, on the use of trade credit.[5] The authors find evidence that financially distressed firms use a significantly larger amount of trade credit to substitute for the lack of alternative sources of financing.

However, Garcia-Appendini and Montoriol-Garriga (2020) argue that the finding by Molina and Preve (2012) is typically limited to the initial stages of financial distress, but it does not stand when a firm is closer to bankruptcy. Accordingly, Garcia-Appendini and Montoriol-Garriga (2020) use a sample of bankrupt firms over the period of 1979-2014 and investigate the use of trade credit as firms approach default. Generally, they find an average decline in the use of trade credit as firms approach a default event (i.e., file for bankruptcy), as suppliers are likely to lose confidence in those firms who become particularly risky.[6]

Thus far, these two studies have enhanced our understanding of the impact of financial distress on the use of trade credit. However, the results of these studies leave the relationship between financial distress and the use of trade credit subject to some

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[5] Following Asquith et al. (1994), they define financial distress as a dummy variable that takes a value of one when the firm's interest coverage ratio is less than one for two consecutive years or less than 80% in any given year.

[6] The measure of default event in this study is based on time-series of up to 15 years until bankruptcy for firms that eventually filed for bankruptcy.

doubt, namely, the positive relation found by Molina and Preve (2012) and the negative relation found by Garcia-Appendini and Montoriol-Garriga (2020). We believe that the relationship between trade credit financing and financial distress may be more nuanced when we investigate this relationship using both market-based and accounting-based measures of financial distress.

Although accounting-based measures of financial distress, such as Altman (1968) and Ohlson (1980), are a suitable proxy for financial distress, they are subject to criticism of their accuracy in predicting financial distress. For example, Agarwal and Taffler (2008) suggest that accounting-based measures of financial distress are based on the past performance of firms and may not be informative in predicting the future. Furthermore, Hillegeist et al. (2004) argue that accounting-based models are likely to be limited in predicting financial distress, because financial statements used in those models are developed under the going-concern principle, which assumes that the firm is not expected to file for bankruptcy. In addition, the accounting information on which these measures are based is subject to manipulation by management (Agarwal and Taffler, 2008).

Market-based measures of financial distress are likely to outperform accounting-based measures, since such measures counter most of the above criticisms of the accounting-based measures. In particular, market-based measures of financial distress are likely to reflect all of the information contained in accounting statements, as well as information that is not contained in accounting statements (Hillegeist et al., 2004). In addition, market variables are unlikely to be affected by the accounting policies of a firm. Furthermore, market prices are likely to reflect future expected cashflows and, thus, should be more appropriate in predicting the future (Agarwal and Taffler, 2008).[7] For the reasons mentioned above, we extend the work of Molina and Preve (2012) and Garcia-Appendini and Montoriol-Garriga (2020) to examine the link between the use of trade credit and financial distress, using both market-based and accounting-based measures of financial distress.

Moreover, there is a concern that financial distress is also endogenously related to the use of trade credit; it may be that increasing the use of trade credit increases financial distress, while an increase in financial distress could bring about an increase in the use of trade credit. Furthermore, it is possible that there is some unobserved variable that

[7] See Agarwal and Taffler (2008) for a more detailed description of comparing the performance of market-based and accounting-based distress prediction measures.

varies across time and drives both trade credit and financial distress. In addition, prior research (e.g., Bris et al., 2005; Stromberg, 2000; Thorburn, 2000) shows that firm characteristics have significant effects on firms' decisions to get into distress/bankruptcy and their choices of bankruptcy outlets. This self-selection effect is another concern. These issues of endogeneity have, to our knowledge, not been considered in the prior studies. Taken together, previous studies that examine the impact of financial distress on the use of trade credit have used either relatively poor proxies for financial distress or misspecified models, ignoring that financial distress is endogenous. Thus, we contribute to the literature and extend prior studies by properly addressing the endogenous association between financial distress and the use of trade credit. In the next subsection, we explain our research questions and formally develop our hypotheses.

2.2.2 Hypothesis Development

Based on different strands of the literature reviewed above, we develop our testable hypotheses regarding the impact of financial distress on the use of trade credit. When firms face financial distress, their ability to access sources of financing is limited, as capital providers may be concerned about the default risk, which makes them less willing to extend additional financing. In this vein, trade credit is likely to substitute for other sources of financing when the latter is unavailable (Meltzer, 1960; Petersen and Rajan, 1997). There are several reasons why financially distressed firms are more likely to substitute other sources of financing with supplier's trade credit.

First, suppliers of financially distressed firms are expected to have the incentive to work as liquidity providers for these firms, due to the financing advantages that suppliers have over traditional financial institutions. Such advantages include suppliers' informational advantage over financial institutions in evaluating the creditworthiness of their customers. In particular, informational advantage arises because suppliers can monitor their customers' credit quality through payment terms selected by them, either choosing to pay early (get a cash discount) or to delay the payment (and forgo a cash discount). When suppliers offer trade credit, the high implicit interest rate in trade credit acts as a screening device to identify the probability of default by the customer (Smith, 1987). Suppliers not only assess their customers' creditworthiness in credit terms; they can also obtain information about their customers because they visit their customers' premises more regularly than financial institutions. Also, suppliers can observe the size of customers' orders and they frequently engage in the same, or a related, industry as their customers (Biais and Gollier, 1997; Petersen and Rajan, 1997; Jain, 2001).

This informational advantage gives the suppliers advantages to identify whether their customers are facing a low or high probability of default. Such an advantage is crucial to enabling suppliers to protect the non-salvageable investments in their customers (Smith, 1987). Alternatively, suppliers can benefit from their superior information about their customers by conveying this information to financial institutions, to reduce bank credit rationing. This enables both suppliers and customers to share the surplus extracted from the financial institution to cover the business relationship. Suppliers can convey this information by offering more trade credit to their distressed customers, which gives the financial institution a credible signal about the creditworthiness of those customers and will, therefore, induce them to lend (Biais and Gollier, 1997). Thus, to the extent that suppliers may be able to recognise whether or not their customers face temporary financial distress, suppliers tend to be more willing to offer trade credit to their customers facing temporary financial problems.

In addition to the informational advantage of suppliers, they also have a financing advantage over traditional financial institutions in enforcing the repayment of credit. Under the assumption that suppliers have strong market power, financially distressed firms are more likely to repay their suppliers than to repay the financial institutions. In particular, suppliers are more willing to help their financially distressed customers because they can enforce payments of credit by threatening to halt future supplies of the inputs in the case of default. This is especially so when the products provided by suppliers have fewer alternatives, such as differentiated inputs, which are more costly to replace (Petersen and Rajan, 1997; McMillan et al., 1999; Cuñat, 2007).

An alternative view of the enforceability power of debt repayment is that even though suppliers know that their customers are in default, they are likely to provide trade credit to those customers due to their liquidation advantage. More specifically, in the case of a customer default, suppliers have an advantage in their ability to liquidate the goods sold to their customers on credit and resell those goods to other customers (Frank and Maksimovic, 2005; Fabbri and Menichini, 2010). Traditional financial institutions can also reclaim their customers' assets to pay off their loans. However, if suppliers already have a network for selling their goods, their costs of repossessing and resale are likely to be lower than that of traditional financial institutions. This advantage is expected to vary depending on the type of goods supplied and how much the customer transforms the goods. The less the goods are transformed by the customer, the greater the advantage suppliers will have over traditional financial institutions in liquidating their customers in the case of default (Petersen and Rajan, 1997).[8] Overall, the above-mentioned arguments suggest that the financing advantages of suppliers could explain why suppliers help their financially distressed customers whose access to other sources of financing is limited.

Second, suppliers are likely to work as liquidity providers to their distressed customers, not only because of their financing advantages, but because suppliers have the incentive to promote their sales (e.g., Brennan et al., 1988). Specifically, under the assumption that suppliers operate in low competition markets or have high bargaining power, they are likely to find it profitable to provide a subsidy for risky customers in the form of highly-priced trade credit to increase their profit margin (Brennan et al., 1988; Petersen and Rajan, 1997). The implicit interest rate involved in trade credit is attractive only to financially distressed firms, for whom access to the credit market is significantly constrained. However, financially healthy firms, who have better access to cheaper sources of financing, are likely to view trade credit as an expensive source of financing, thereby relying less on such a source of financing (Petersen and Rajan, 1994; Brennan et al., 1988).

Finally, suppliers do not offer trade credit to their distressed customers to increase their profit margin solely; they also have the incentive to provide trade credit to benefit from a continued relationship with their financially distressed customers in the long run (Petersen and Rajan, 1997). This is especially true when distressed customers have bargaining power in the market, in that they are costly to replace. This bargaining power makes suppliers more willing to give their financially distressed customers a large renegotiation of concessions in the form of liquidity. This is because suppliers have an implicit equity stake in their distressed customers and expect additional sales in the future from the business relationship with those distressed customers (Wilner, 2000). Suppliers are likely to help their financially distressed customers if the continuation value for the supplier exceeds the cost of bailing out these customers (Cuñat, 2007). Likewise, suppliers are also expected to help their distressed customers when they make

[8] However, even though the suppliers are able to liquate their customers, the repossession advantage is limited in the U.S. This is because priority rules and bankruptcy laws would severely limit the suppliers' ability to liquidate their default customers. Indeed, trade credit is likely to be non-senior debt and suppliers can repossess their product that has not been diverted (from inputs to cash) only within 10 days from the sale (Garvin, 1996; Giannetti et al., 2011).

high relationship-specific investments, such as providing the customer with special machinery or specific technology and building a plant close to their customers (Dass et al., 2014). In fact, relationship-specific investments would create a hold-up problem arising from incomplete contracts between suppliers and customers (Klein et al., 1978; Tirole, 1999; Harbaugh, 2001; Fee et al., 2006). Thus, suppliers who make relationship-specific investments in their distressed customers are likely to face switching costs if they do not help those customers, as the survival of those customers is crucial to completing the business relationship between them.

Overall, given the different motivations for trade credit usage, suppliers are expected to help those of their customers whose access to traditional sources of financing is limited when they are in financial distress. Suppliers may expect the level of financial distress of their customers is not extremely high and, thus, they are more willing to help their customers for the above-mentioned reasons. Our first hypothesis is stated as follows:

H1*: An increase in financial distress leads to an increase in the use of trade credit.*

Financial distress may, however, also contribute to decreasing the use of trade credit. The prior literature on financial distress argues that financially distressed firms are likely to face problems with their suppliers. Baxter (1967) finds that firms in financial distress are expected to have difficulty obtaining trade credit from their suppliers. Moreover, Altman (1984, p.1072) shows that suppliers are likely to be less willing to supply products to their distressed customers "except under fairly significant restrictions and higher costs, e.g., cash on delivery". Furthermore, Andrade and Kaplan (1998) find that one-third of the financially distressed firms in their sample experienced difficulties with suppliers. All these arguments suggest that suppliers, like other providers of financing, may withdraw their support as they progressively lose confidence in their distressed customers (Smith, 1987; Garcia-Appendini and Montoriol-Garriga, 2020). Moreover, the informational advantage of suppliers over financial institutions may facilitate an early exit from a distressed relationship, as it enables suppliers to sort low- from high-default risk customers (Smith, 1987; Biais and Gollier, 1997). Alternatively, under the assumption that bankruptcy laws probably limit the suppliers' ability to liquidate their customers in the case of default (Garvin, 1996), suppliers are expected to be less willing to offer trade credit to their distressed customers. Thus, as an alternative hypothesis, firms in financial distress are likely to receive less trade credit from their suppliers.

In addition to exploring whether financial distress affects the use of trade credit, we develop our testable hypotheses for our cross-sectional heterogeneity tests of whether the positive relationship between financial distress and the use of trade credit is stronger for some firms than in others. The objective of these analyses is to offer more insight into whether the financing advantages of suppliers over financial institutions drive the suppliers to help their financially distressed customers, whereas financial institutions or capital providers are reluctant to provide funds for these firms because of the fear of default. In particular, we explore whether the effect of financial distress on the use of trade credit financing varies with the level of information opacity and social trust.

First, the effect of financial distress on the use of trade credit is likely to vary with the level of information opacity. Under the assumption that suppliers have an informational advantage over financial institutions in identifying future defaults of their customers more quickly than financial institutions (Smith, 1987; Biais and Gollier, 1997), firms are likely to rely more on trade credit when they have a more opaque information environment. It is expected that financially distressed firms in more opaque information environments face more difficulties in obtaining external financing from their capital providers. This is because high information opacity makes it more difficult for capital providers to assess the credit quality of distressed firms, which, in turn, leads capital providers to be reluctant to provide finance to such firms. In contrast, financially distressed firms with less opaque information environments are likely to provide sufficient and more reliable information that helps capital providers to assess their credit risk, which, in turn, allows these firms to have better access to sources of financing. Given the high cost of trade credit (Smith, 1987; Petersen and Rajan, 1994, 1995, 1997; Cuñat, 2007), distressed firms with less information opacity are expected to prefer to use cheaper sources of financing to replace trade credit. Accordingly, to the extent that suppliers are likely to help their distressed customers because they have the ability to assess and monitor the creditworthiness of their distressed customers better than financial institutions, we expect the positive relationship between financial distress and the use of trade credit to be stronger (minimal) for firms with more (less) information opacity. This hypothesis is stated as follows:

H2: *The positive impact of financial distress on trade credit is greater for firms with a more opaque information environment.*

Second, the impact of financial distress on the use of trade credit is also likely to vary with the level of social trust in the region of the distressed firm's headquarters. Early work by Williamson (1993) shows that social trust can influence the interaction between firms and their stakeholders. In particular, prior studies show that firms headquartered in high social trust (or capital) regions are less likely to misreport financial information and, thus, commit fewer financial frauds compared to firms headquartered in low social trust regions (Jha, 2019). Market participants perceive firms from high social trust regions to be trustworthy and honest, which, in turn, helps firms from high social trust regions to access sources of financing at a relatively lower cost (Guiso et al., 2004). Several empirical studies show that access to alternative sources of financing is easier and cheaper for firms headquartered in high social trust regions. For example, Hasan et al. (2017) show that firms headquartered in high social trust regions have lower loan spreads, lower at-issue bond spreads and prefer public bonds over bank loans. Moreover, Gupta et al. (2018) find that firms headquartered in high social trust regions have a lower cost of equity than firms headquartered in low social trust regions. These arguments suggest that capital providers are likely to be able to assess the creditworthiness of distressed firms headquartered in high social trust regions, as capital providers view high social trust as providing environmental pressure that mitigates moral hazards and information asymmetry problems. As a result, distressed firms in high social trust regions are expected to have better access to sources of financing already and, thereby, rely less on trade credit.

In contrast, distressed firms in low social trust regions are expected to rely more on trade credit because they have limited access to other sources of financing, as firms in these regions are likely to misbehave or take actions that may harm capital providers. Suppliers might be subject to opportunistic behaviours by their distressed customers in low social trust regions. However, given that suppliers have better information about their distressed customers and lower borrowers' opportunism in the case of default over traditional financial institutions, they are expected to be less affected by any harmful actions taken by their distressed customers in low social trust regions. Thus, suppliers are expected to be more willing to offer trade credit to their distressed customers in low social trust regions. Accordingly, if distressed firms face difficulties accessing sources of financing because capital providers do not trust them, then the positive impact of financial distress on the use of trade credit is expected to be greater for firms headquartered in low social trust regions. This hypothesis is stated as follows:

H3*: The positive impact of financial distress on trade credit is greater for firms headquartered in low social trust regions.*

Although suppliers are more willing to help their distressed customers because they have financing advantages over traditional financial institutions, they may have incentives to provide trade credit to their distressed customers only under the assumptions that the level of financial distress is not extremely high and that their distressed customers may not affect their value negatively. Thus, financially distressed firms cannot always rely on trade credit financing. To investigate this issue, we develop two additional hypotheses on whether being a major customer leads to an increase in the use of trade credit in the case of financial distress and whether the degree of financial distress affects the use of trade credit.

First, despite the existing literature on trade credit (e.g., Wilner, 2000; Cuñat, 2007) argues that suppliers help their financially distressed customers because they have an implicit equity stake in their customers' business, others (e.g., Cohen and Frazzini, 2008; Hertzel et al., 2008; Jorion and Zhang, 2009; Kolay et al., 2016) argue that suppliers may incur significant losses when their major customers become financially distressed or declare bankruptcy. A growing body of research on the customer-supplier relationship (Hertzel et al., 2008; Kolay et al., 2016; Jorion and Zhang, 2009) documents negative suppliers' abnormal stock returns to the announcement that their major customers have declared bankruptcy. Jorion and Zhang (2009), for example, find that firms extending trade credit to their major customers who eventually file Chapter 11 bankruptcy suffer from significant negative abnormal returns. They also show that when a firm's shareholders recognise the negative news about its major customers, they adjust their valuation downward. Similarly, Cohen and Frazzini (2008) and Alldredge and Cicero (2015) document that shareholders of the supplier firm predict their firm's returns based on the past abnormal returns of the major customers. Shareholders of the supplier firm have information about the major customers because information on the customer-supplier relationship is publicly available, as suppliers are required to disclose information about those customers in their financial statements (Cohen and Frazzini, 2008). In particular, since 1976, the Statement of Financial Accounting Standards No. 14 (SFAS 14) of the Financial Accounting Standard Board (FASB) has required suppliers to disclose external customers that individually account for 10% or more of their sales (Kale and Shahrur, 2007).

Thus, under the assumption that being a major customer can affect suppliers' performance, we expect that suppliers are also more concerned about the financial distress of their major customers and may, therefore, offer less trade credit to financially distressed major customers. On the other hand, suppliers may be more willing to provide trade credit to their major customers who are not financially distressed. Given that prior literature shows that major customers who are in distress affect the supplier's firm valuation, non-distressed major customers are also likely to be perceived favourably by a supplier firm's investors. Further, non-distressed major customers are likely to have greater bargaining power, forcing their suppliers to offer more trade credit. Thus, non-distressed major customers may use their bargaining power to extract significant price concessions and trade credit provision (Snyder, 1996). This hypothesis is stated as follows:

H4: *The positive impact of financial distress on trade credit is weaker when the firm is a major customer.*

Second, suppliers may also be less willing to provide liquidity to their distressed customers when their customers become particularly risky (Garcia-Appendini Montoriol-Garriga, 2020). Despite prior literature on trade credit arguing that suppliers have a financing advantage over financial institutions in liquidating their customers in the case of default (e.g., Petersen and Rajan, 1997; Frank and Maksimovic, 2005; Fabbri and Menichini, 2010), trade credit may lack contractual seniority and formal collateral (Garvin, 1996; Giannetti et al., 2011). Due to the lack of these protective actions, recovery rates of trade credit are potentially low in the event of a default. Further, under the assumption that the informational advantage of suppliers helps them sort low- from high-default risk customers (Smith, 1987), suppliers are expected to stop the supply of goods to their distressed customers if the default risk is very high. This is especially true in the absence of customer-specific non-salvageable investment, as those customers are expected to be less valuable when they have a high level of financial distress (Smith, 1987). Thus, we expect that distressed firms cannot rely on trade credit financing when the level of financial distress is very high. This suggests that the positive relationship between trade credit use and financial distress will be mitigated at high levels of distress. This hypothesis is stated as follows:

H5: *There is an inverted U-shaped relation between financial distress and trade credit use.*

2.3 Data and Research Design

This section discusses the data and key variables of the study. Subsection 2.3.1 describes the data sources and sample selection. Subsection 2.3.2 discusses the research design, including the empirical model, dependent variable, financial distress measures, and control variables. Subsection 2.3.3 discusses the descriptive statistics.

2.3.1 Data Sources and Sample Selection

Our initial sample consists of U.S. public firms over the period 1975-2017 from Compustat North America. From this database, we obtain our annual accounting data.[9] We then match these data with the Centre for Research in Security Prices (CRSP) files that provide data on firms' stock prices. We include in our sample all firms with common stocks listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the Nasdaq Stock Market (NASDAQ). Next, we exclude firms from regulated industries. In particular, we exclude all firms operating in the financial sector (standard industrial classifications (SIC) codes 6000-6999), non-classifiable establishments (SIC codes 9000-9999) and utility firms (SIC codes 4900-4999).

We further use additional databases for other variables used in our cross-sectional analysis. We use data from the Institutional Brokers Estimate System (IBES) to obtain the number of analysts following a firm.[10] We also use data from Brown's website that provides annual data on the probability of informed trading (PIN) calculated by Brown and Hillegeist (2007). Finally, we use data from the Northeast Regional Centre for Rural Development in the College of Agricultural Sciences at Pennsylvania State University to obtain Rupasingha et al’s. (2006) county-level social capital index.

To reduce the impact of misreported data in our analysis, we drop firm-year observations when total assets, sales, cost of goods sold and accounts payable have negative values, or when accounts payable exceed the total book value of assets. We further drop observations of the main variables used in our study with missing values. Next, to eliminate outliers, all continuous variables adopted in our study are winsorized at the 1st and 99th percentiles. Moreover, we adjust the value of total assets and net sales to inflation, to make them more comparable over time.[11]

[9] Our sample period starts from 1975 due to the relatively limited coverage of the accounting data before 1975.
[10] We replace missing values for the number of analysts with zero.
[11] Assets and sales are adjusted for inflation using Consumer Price Index (CPI) and are expressed in 2016 dollars.

Our sample consists of 106,576 firm-year observations and includes 10,402 unique public firms over the period 1975-2017. However, since we lag all explanatory variables, our final sample consists of 9,528 unique public firms with a total of 99,019 firm-year observations over the period 1976-2017. All variable definitions are in Table 2.A1 in the Appendix.

2.3.2 Research Design

2.3.2.1 Empirical Model

To examine our main hypothesis, "H1", that financial distress increases the use of trade credit financing, we estimate the following regression model:

$$AP/AT_{it+1} = \beta_0 + \beta_1 Distress_{it} + \theta' X_{it} + \varepsilon_{it}, \qquad \text{Eq. 2.1}$$

Where i indicates firm and t indicates a year. The dependent variable (AP/AT) is the ratio of accounts payable to total assets, for reasons set out below. The explanatory variable (Distress) is financial distress. The control variables (X) are used to control for some firm-specific factors, described in section 2.3.2.4, that are likely to affect the use of trade credit.

We start our baseline regression by controlling for the industry fixed effect (SIC three-digit). We also control for year fixed effects to reduce the impact of the time trend and changes in economic conditions. However, since our model is likely to lead to biased estimation, we deal with unobserved firm heterogeneity that is time-invariant by controlling for the firm fixed effect, rather than the industry fixed effect.[12] We further lag all the right-hand side variables of the model by one year to allow them to affect the use of trade credit. For example, it could be that the increase in trade credit caused by distress may not manifest itself in the same year as the distress (Molina and Preve,2012).[13] Finally, we control for possible heteroscedasticity by using clustered standard errors at the firm level. According to our first hypothesis, "H1", we expect the coefficients on Distress to be positive and significant ($\beta 1>0$).[14]

[12] To better address potential endogeneity issues arising from time-invariant unobservable factors at the firm level, we use firm rather than industry fixed effects in all subsequent tests.

[13] Our results remain qualitatively the same when we use the contemporaneous value of the independent variables.

[14] The regression models we use to test H2, H3, and H4 are similar to Equation 2.1, except that we further include interaction terms to capture the cross-sectional heterogeneity. For H5, we add the quadratic term of financial distress measures to Equation 2.1.

2.3.2.2 Measuring the Use of Trade Credit.

Different proxies are used in the literature to measure the use of trade credit. Several studies (e.g., Petersen and Rajan, 1997; Fisman and Love, 2003; Cuñat, 2007; Giannetti et al., 2011; Abdulla et al., 2017; McGuinness et al., 2018) use the ratio of accounts payable to total assets as a proxy to scale the use of trade credit. Although measuring trade credit with the ratio of account payables to total assets is standard in the literature (Elliehausen and Wolken, 1993; Love et al., 2007), other studies (e.g., Love et al., 2007) measure the use of trade credit as the ratio of accounts payable to the cost of goods sold to capture the importance of trade credit in the financing of economic activity. However, for firms in the manufacturing sector, which constitute over 50% of our sample, the cost of goods sold should include direct labour costs (McConnell et al., 2019). This item is not available in Compustat; therefore, like previous research, we cannot calculate the entire costs of goods sold for manufacturing firms. We, therefore, use the ratio of accounts payable to total assets as our main measure of the use of trade credit. Nevertheless, we use the ratio of accounts payable to the cost of goods sold (available in Compustat) as a robustness check.[15]

2.3.2.3 Measures of Financial Distress

Prior literature suggests several measures to predict financial distress using information from financial statements (such as profitability, working capital, and leverage) or market information (such as stock price). However, there has been an extensive debate about whether accounting-based measures or market-based measures perform better to predict financial distress (Hillegeist et al., 2004). For this reason, we use alternative measures of financial distress to check for the robustness of results.

In our study, we use two main measures of financial distress. Our first measure is a market-based model, Merton's (1974) distance to default model (DD). This measure is widely employed in the literature and has been shown to be an appropriate measure of financial distress (e.g., Vassalou and Xing, 2004; Hillegeist et al., 2004; Duffie et al., 2007; Bharath and Shumway, 2008; Campbell et al., 2008). The model is based on the theoretical work of Black and Scholes (1973) and Merton (1974), which assumes that the value of the firm's equity is a call option on the underlying value of the firm assets, with a strike price value that is equal to the face value of the firm's debt. The firm is in

[15] The use of alternative measures of trade credit is formally addressed in Subsection 2.4.2.1.

default when the face value of debt (strike price) is above the value of the assets (i.e., the call option is unexercised). In our study, we use the naïve distance to default, as defined by Bharath and Shumway (2008), rather than the original distance to default measure that requires a numerical solution to solve two nonlinear equations and implementing an iterative process based on the Black–Scholes–Merton pricing model. In fact, Bharath and Shumway (2008) show that a naïve model that is based on the functional form of Merton's model performs better than the original distance to default measure.[16,17] A higher value of Merton's distance to default indicates a lower level of financial distress.

Our second measure of financial distress is an accounting-based model, which is the Altman (1968) Z score. This model is a weighted combination of five financial ratios used to predict bankruptcy by employing multiple discriminant analysis (MDA). These five ratios are profitability, leverage, liquidity, activity and solvency. For this weighted combination (the so-called Z score), Altman (1968) identifies the "cut-off" point, or optimum Z value, to classify firms into financially distressed or healthy categories. Firms with a Z score below 1.81 fall into the "distressed" category, while firms with a Z score greater than 2.99 are all "non-distressed". Overall, a higher value of the Altman Z score reflects a lower level of financial distress.[18, 19]

Given that each measure has a different outcome, we follow prior studies (e.g., Hillegeist et al., 2004) and convert our two measures of financial distress into probabilities to ease the interpretation of the results. We convert Merton’s (1974) Distance-to-Default model into probability of default using the normal cumulative density function of Merton’s (1974) Distance-to-Default multiplied by -1. However, the Altman (1968) Z score is estimated using multiple discriminant analysis (MDA), which is based on scores rather than on probabilities. Nevertheless, under normality assumptions, multiple discriminant analysis (MDA) and the logit model are closely related to each other (McFadden, 1976). Thus, following Hillegeist et al. (2004), we convert Altman’s (1968) Z score into probabilities using the logistic cumulative

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[16] The calculation of the Merton (1974) distance to default model (based on the naïve model) is described in Table 2.A.1 in the Appendix.

[17] Our results remain qualitatively similar if we use the original distance to default measure. See Table 2.A3 in the Appendix.

[18] The calculation of Altman’s (1968) Z score is described in Table 2.A1 in the Appendix.

[19] Following Graham (1996) and MacKie-Mason (1990), we use the modified Altman’s Z-Score as a robustness check, which omits the ratio of market equity to book debt because we control for the ratio of market to book value and leverage in our model. Our results remain qualitatively similar if we use the modified Altman Z score. See Table 2.A4 in the Appendix.

distribution function of Altman’s (1968) Z score multiplied by -1. Computed this way, Altman’s (1968) Z score can represent the default probabilities. Accordingly. a higher value of the probability of default based on both measures of financial distress indicates a higher level of financial distress.

2.3.2.4 Control Variables

Consistent with prior literature, we include the following control variables in our model: firm size (Firm Size), firm age (Firm Age), tangibility (Tangibility), cost of goods sold to total assets (Cost of Goods Sold), sales growth (Negative Growth and Positive Growth), market-to-book ratio (MTB), capital expenditure (Capital Expenditure), research and development expenditures (R&D), return on assets (ROA), cash holdings (Cash Holding), financial leverage (Leverage), and market share (Market Share). These control variables capture a wide range of firm characteristics that are likely to be associated with firms' use and supply of trade credit financing. First, the firm's use of trade credit is expected to be associated with its creditworthiness and information asymmetry, which can be proxied by firm size, age and tangibility (Petersen and Rajan, 1997). Small and young firms and firms with less tangible assets are likely to use more trade credit because they have limited access to other sources of financing. Suppliers are more likely to offer trade credit to those firms because they have financing advantages over traditional financial institutions in assessing the creditworthiness of these firms (Petersen and Rajan, 1997). Therefore, we expect that firm size, age, and tangibility will be negatively related to the use of trade credit.

In addition, firms with high growth opportunities are also likely to be more constrained and have high information asymmetry, and, thus, they are expected to rely more on trade credit (Cuñat, 2007). Instead, firms with high growth opportunities are likely to use trade credit to finance their new investments in current assets (Petersen and Rajan, 1997). We use a wide range of firm characteristics that could be related to growth opportunities used by previous studies on trade credit (e.g., Petersen and Rajan, 1997; Abdulla et al., 2017; Zhang, 2019; D'Mello and Toscano, 2020; Shang, 2020). In particular, we use sales growth, market to book ratio, capital expenditures, and R&D expenditures as proxies for growth opportunities. We expect trade credit to be positively related to these variables. Moreover, for sales growth, we follow Petersen and Rajan (1997) and distinguish between positive and negative growth rates. Thus, we expect trade credit to be positively (negatively) correlated with positive (negative) growth rates.

We also control for the internal source of financing. Petersen and Rajan (1997) and Dass et al. (2015) show that net income represents an internal source of financing, which is likely to affect the use of trade credit. Given that firms are expected to follow a financial "pecking order" of their sources of financing (Myers and Majluf, 1984), firms are likely to prefer to use internal sources of financing and then resort to external sources. Since trade credit is an external source of financing and is expensive, firms are likely to use trade credit when their internal sources and other cheaper external sources are exhausted (Petersen and Rajan, 1997). We, therefore, include ROA as a control variable in our model and expect ROA to be negatively related to trade credit.

Further, prior studies on trade credit (e.g., Garcia-Appendini and Montoriol-Garriga, 2013; Dass et al., 2015; Gonçalves et al., 2018) argue that firms that hold a higher level of cash have higher liquidity and are subject to fewer financing constraints relative to those that hold lower cash, thereby, relying less on trade credit. We, thus, control for cash holding and expect cash holding to have a negative impact on the use of trade credit. In addition, we control for a possible substitution effect between trade credit and public debt markets. Prior literature on trade credit (e.g., Petersen and Rajan, 1997; Nilsen, 2002; Garcia-Appendini and Montoriol-Garriga, 2013) argues that when firms' access to public debt markets is limited, they are likely to use trade credit as a substitute for these sources of financing. We, therefore, include leverage in our model as a proxy for the substitution effect between trade credit and public debt markets. We expect leverage to have a negative relationship with the use of trade credit.

In addition, firms with stronger bargaining power in the market are likely to force their suppliers to provide more trade credit. In particular, firms with a high market share could have stronger bargaining power in the business relationship with their suppliers. Thus, they are expected to force suppliers to offer more trade credit, as suppliers are likely to have a large implicit stake in their customers' business (Peterson and Rajan, 1997; Wiliner, 2000; Klapper et al., 2012). We, therefore, include a firm's market share in our model as a proxy for bargaining power. We expect market share to be positively related to trade credit. Finally, because firms that buy more are likely to do so by using more trade credit (D'Mello et al., 2020), we control for the ratio of cost of goods sold to total assets in our model. We expect the cost of goods sold ratio to positively affect the use of trade credit.

2.3.3 Descriptive Statistics

We now turn to the descriptive statistics for the main variables used in this study. Panel A of Table 2.1, presents the distribution of our sample by year. The number of firms ranges from a minimum of 1,386 in the year 2017 to a maximum of 3,218 in the year 1997, which represents about 1.40%-3.25% of the entire sample. The maximum number of observations we use in our analysis is equal to 99,019 over a 42-year period. It is worth noting that the annual number of firm-year observations reached its peak in 1997. However, after 1997, the annual number of firm-year observations starts to decline. Generally, the number of observations is distributed fairly evenly across years. Panel A of Table 2.1, further shows the means of trade credit by year. The mean of accounts payable ranges from 7.62% in 2014 to 11.45% in 1978. The mean of trade credit is relatively low after 2000, suggesting that firms relied more on the use of trade credit before 2000.

Panel B of Table 2.1, provides the firm-level summary statistics of our main variables for the full sample. The mean (median) use of trade credit by the sampled firms accounts for 9.47% (7.36%) of their total assets, namely, 9.47 (7.36) dollars of accounts payable for every 100 dollars in total assets. The table also shows that accounts payable to total assets range from 0.49% at the 1st percentile to 42.30% at the 99th percentile. Regarding financial distress measures, Panel B of Table 2.1, also reports the probabilities of default of our financial distress measures. The mean, median, p1 and p99 of the probability of default based on the Merton (1974) model (i.e., Distress_Merton) are 2.11%, 0%, 0%, and 45.20%, respectively, while for the Altman (1963) model (i.e., Distress_Altman) they are 8.80%, 2.53%, 0%, and 99.40%, respectively. The results indicate that each measure of financial distress has different ranges of probabilities of default, which suggests that the values of those measures do not represent the actual probabilities of default. In particular, the Merton (1974) model is converted into probabilities using the cumulative density function of the standard normal distribution (see Hillegeist et al., 2004; Bharath and Shumway, 2008; Campbell et al., 2008). The cumulative density function converts the value of the Merton Distance to Default to zero when its value is above 3.9 and close to one when its value is below -3.9. In our sample, approximately 75% of observations have Merton Distance to Default values greater than 3.9 (not reported). Thus, the estimated values of probability of default based on the Merton model (Distress_Merton) are close to zero for roughly 75% of our observations.[20] However, The Altman Z model is converted into probabilities using the logit model. As mentioned before, the Altman Z score model is estimated using multiple discriminant analysis (MDA), which is based on a score, not a probability. This means that the transformation of the Altman Z score model into probabilities is not strictly correct (Hillegeist et al., 2004). However, multiple discriminant analysis and the logit model are closely related to each other according to normality assumptions (McFadden, 1976). Overall, our summary statistics of financial distress measures are comparable to the prior work (e.g., Hillegeist et al., 2004; Chang et al., 2016; Cornaggia et al., 2017; Anginer and Yildizhan, 2018).

In terms of other firm-specific characteristics, Panel B of Table 2.1, further shows that the mean (median) firm size, "log assets", is 5.3610 (5.2338) (corresponding to approximately \$296 (\$260) million of total assets) with a standard deviation of 1.9483. Firm size is 1.4327 at the 1st percentile and 10.36 at the 99th percentile, which indicates that our sample represents both small and large firms. Also, the mean (median) firm age is 18.42 (15) years, which is 3 years at the 1st percentile and 60 years at the 99th percentile. This suggests that our sample represents both young and mature firms. Further, the tangible assets represent, on average 28.70% (median 23.37%), of the firms' total assets. The ratio of tangible assets is 1.35% at the 1st percentile and 87.90% at the 99th percentile. Panel B of Table 2.1, further shows that the mean (median) cost of goods sold to total assets is 91.70% (76.10%), which is 0.0441 at the 1st percentile and 3.9280 at the 99th percentile. In addition, the average firm has a negative growth of 3.80%, while it has a positive growth of 18.30%. The results indicate that 25% of our sampled firms have negative growth during the sample period. The mean (median) firm has also a market to book ratio, "MTB", of 1.7640 (1.3247), which is 0.5709 at the 1st percentile and 7.6950 at the 99th percentile.

Panel B of Table 2.1, also shows that capital expenditures account, on average 6.50% (median 4.52%), of the firms' total assets. The ratio of capital expenditure is 0.22% at the 1st percentile and 34.80% at the 99th percentile. Further, research and development, "R&D", expenditures account, on average, for 3.72% of the firms' total assets. We find that in more than half of the sample, firm-years do not have R&D expenditures. In addition, the mean (median) firm has a return on assets, "ROA", of 0.67% (4.34%),

[20] Chang et al. (2016) also find similar results that that the estimated values of probability of default based on the Merton model are close to zero for approximately 75% of their observations.

which is negative for 25% of firm-year observations in our sample. Further, the mean (median) firm holds 15% (7.98%) of their assets in cash, with values of 0.03% at the 1st percentile and 76.90% at the 99th percentile. Total debt, "Leverage", accounts, on average 22.30% (median 19.65%), of the firms' total assets, ranging from 0% at the 1st percentile to 86.50% at the 99th percentile. Finally, the mean (median) firm has a market share of 4.81%, which ranges from 0% at the 1st percentile to 67.30% at the 99th percentile. Generally, these figures for firm firm-specific characteristics are comparable to previous studies on trade credit (e.g., Abdulla et al., 2017; 2020; Garcia-Appendini and Montoriol-Garriga, 2019; Shang, 2020) and on corporate finance in general (e.g., Smith, 2016; Billett et al., 2017).

Next, we discuss the descriptive statistic across industries. Panel C of Table 2.1 presents the mean of trade credit and financial distress variables for each of the Fama and French 12 industry categories. We find that most firms in our sample are from the business equipment and manufacturing, accounting for about 23% and 17.58% of our sample, respectively. On the other hand, we find that the least number of firms are from telecommunication and chemicals, accounting for almost 2.64% and 3.55% of our sample, respectively. In terms of the use of trade credit across industries, we find that firms that engage in the retail and wholesale sector rely significantly on trade credit, with mean accounts payable to total assets of approximately 15.18%. This result is consistent with Abdulla et al's. (2017) evidence for U.S. public and private firms. However, firms that operate in the telecommunication sector have the lowest level of trade credit, with mean accounts payable to total assets of about 5.23%.[21] The telecommunication sector also has a relatively high level of financial distress than other industries, with mean Distress_Merton and Distress_Altman of 3.41% and 20.99%, respectively. Generally, the results suggest that financial distress and the use of trade credit varied across industries.

To explore the correlation between the variables used in our research, Panel D of Table 2.1 presents the Pearson correlation coefficients between variables. The table shows the correlation between measures of financial distress is significantly positive. In particular, the correlation between Distress_Merton and Distress_Altman is 30%.

[21] Some studies (e.g., Fisman and Love, 2003; Abdulla et al., 2017) show that firms that operate in the health sector have the lowest level of trade credit, as the use of trade credit is unpopular for medical equipment and drugs companies, due to the difficulty for suppliers to resell these products in case of default. We find that this sector uses a low level of trade credit, but it is not the lowest sector. This finding is consistent with Abdulla et al. (2017) for a sample of only public firms.

However, this correlation is not particularly strong, suggesting that the use of such additional measures of financial distress is warranted to examine the impact of financial distress on the use of trade credit. Moreover, Panel D of Table 2.1 shows the correlation between financial distress and the use of trade credit. The two measures of financial distress (i.e., Distress_Merton and Distress_Altman) are positively and significantly related to the use of trade credit (i.e., accounts payable to total assets). This finding is in line with our first hypothesis, "H1", that financially distressed firms rely more on trade credit financing. The correlation matrix also shows that Cost of Goods Sold, Leverage, and Market Share are positively related to the use of trade credit. On the other hand, Firm Size, Firm Age, Tangibility, Negative Growth, Positive Growth, MTB, Capital Expenditure, R&D, ROA, Cash Holding are negatively associated with trade credit. Overall, the correlation coefficients of the variables used in the study are fairly small, mitigating concerns regarding multicollinearity. To further ensure that multicollinearity is not a problem, we also calculate the Variance Inflation Factors (VIF) for each independent variable in our multivariate regressions. The mean of VIFs does not exceed 3, which indicates that multicollinearity does not appear to pose any problems in our analyses.[22]

Thus far, we have described the main variables used in this study; In the next subsection, we discuss our empirical results regarding the relationship between financial distress and the use of trade credit.

[Insert Table 2.1 here]

2.4 Empirical Results

We now turn to an empirical examination of the impact of financial distress on the use of trade credit. We start with our main results in Section 2.4.1. We then conduct robustness tests in Section 2.4.2. In Section 2.4.3, we address the endogeneity concerns. In Section 2.4.4, we conduct cross-sectional analysis, while in Section 2.4.5, we conduct further analysis.

[22] Hair et al. (2009) show that VIF less than 10 indicates inconsequential collinearity. See Table 2.A2 in the Appendix for variance inflation factors.

2.4.1 Main Results

In this section, we start with a univariate analysis in a sample of distressed firms and non-distressed firms. We then test our main hypothesis in a multivariate regression framework.

2.4.1.1 Univariate Analysis

To explore differences in the levels of use of trade credit and some firm-specific characteristics among financially distressed and non-distressed firms, Table 2.2 reports the univariate analysis. We classify firms into distressed and non-distressed firms based on the Merton model (Columns 1-3). We classify a firm as being distressed (i.e., Distssred1=1) if, in a given year, it is in the top quartile of the sample's distribution of the Distress_Merton. Distressed firms (i.e., Distssred1=1) have a mean trade credit of 11.38%, which is greater than the figure for non-distressed firms (Distssred1=0), which have a mean of 8.82%. The difference between the mean accounts payable ratios of distressed and non-distressed firms based on the Merton model is approximately 2.56 percentage points and is statistically significant at the 1% level. This finding provides an initial indication that financially distressed firms rely significantly more on trade credit than non-distressed firms, which is consistent with our first hypothesis "H1". In addition to the differences in the levels of trade credit, there are other notable differences between distressed and non-distressed firms. Distressed firms tend to be smaller, younger, have lower growth, lower market to book ratio, lower capital expenditures, lower R&D expenditures, unprofitable, hold less cash, and have a lower market share. Further, they have a higher level of cost of goods sold, more tangible assets, and higher levels of leverage.

We also classify firms into distressed and non-distressed firms based on the Altman Z score (Columns 4-6). We define a firm as being distressed (i.e., Distssred2=1) if the firm's Altman Z score is below 1.81, and zero otherwise. Again, Columns (4)-(6) of Table 2.2 shows that the results using the Altman model are qualitatively similar to those using the Merton model. In particular, we find that Distressed firms (i.e., Distssred2=1) have a mean trade credit of 9.8%, which is greater than the figure for non-distressed firms (Distssred2=0), which have a mean of 9.6%. The difference between the mean accounts payable to total assets of distressed and non-distressed firms based on the Altman model is 0.20 percentage points and is statistically significant at the 5% level.

[Insert Table 2.2 here]

2.4.1.2 Multivariate Analysis – Baseline Regression Results

We now move on with the formal regression analysis (Equation 2.1) of the impact of financial distress on the use of trade credit "H1". Table 2.3 reports our baseline results. We estimate different regressions with industry (SIC-3 digit) and year fixed effects in Columns (1) and (3) and with firm and year fixed effects in Columns (2) and (4). In all regressions, the standard errors are clustered at the firm level. In Columns (1) and (2), we report the result when financial distress is measured using the Merton (1974) model (Distress_Merton), while in Columns (3) and (4), we report the result when financial distress is measured using the Altman (1968) Z model (Distress_Altman). Table 2.3 shows that all measures of financial distress attract positive and significant coefficients across all models, indicating that firms that are financially distressed use more trade credit as a short-term source of financing. More specifically, in Column (1), the coefficient on Distress_Merton is positive (0.0416) and significant at the 1% level (t-statistic=8.15). Also, when using firm fixed effects (Column 2), the coefficient on Distress_Merton is positive (0.0187) and significant at the 1% level (t-statistic=of 4.93). Similarly, when using the Altman model, the results suggest a positive relation between financial distress and the use of trade credit. In particular, in Columns (3) and (4), the coefficient on Distress_Altman is positive (0.0362 and 0.0204, respectively) and significant at the 1% level (t-statistics =11.20 and 7.23, respectively).

Using the coefficient estimate of Distress_Merton from Column (1) (industry fixed effects) to gauge the economic significance, a one-standard-deviation increase in the probability of default as proxied by the Merton model (0.0734) is associated with a 0.30 percentage points (0.0416×0.0734) increase in the accounts payable to total assets. This magnitude is a 3.22% (4.15%) increase relative to the mean (median) accounts payable to total assets of 0.0947 (0.0736) per standard deviation increase in the probability of default. On the other hand, the economic significance, when we control for firm and year fixed effects, is slightly smaller: a one-standard-deviation increase in the probability of default is associated with a 0.13 percentage points increase in the accounts payable to the total assets ratio. This amount is a 1.45% (1.86%) increase relative to the mean (median) accounts payable to total assets. Further, when using the Altman model, a one-standard-deviation increase in the probability of default (0.1761) is associated with 0.63 percentage points (or 0.36 percentage points when we control for firm fixed effects) increase in accounts payable to total assets. While there are differences in the size of coefficients on different models and financial distress measures, they are clearly consistent: there is a positive relationship between financial distress and the use of trade credit.

Table 2.3 also indicates that the signs of the estimated coefficients on the control variables are generally consistent with the literature (e.g., Petersen and Rajan, 1997; Cuñat, 2007; Klapper et al., 2012; Garcia-Appendini and Montoriol–Garriga, 2013; Abdulla et al., 2016). As expected, the coefficient on Firm Size is negative and significant in all columns. Further, Firm Age is negatively related to the use of trade credit and significant in columns with industry fixed effects. Also, Tangibility has a negative and significant coefficient in all columns. These results indicate that smaller, younger firms and firms with lower tangible assets use more trade credit.

We also find that the use of trade credit is positively related to the cost of goods sold and statistically significant in all columns, indicating that firms that buy more use more trade credit (D'Mello et al., 2020). Moreover, Positive Growth has a significantly positive coefficient in all columns. However, Negative Growth also has a significantly positive coefficient when we control for firm fixed effects, suggesting that firms with negative growth options rely more on trade credit. Also, the market to book ratio (MTB) has a positive impact on trade credit. However, it is not significant when we control for firm fixed effects. We further find that the coefficient on Capital Expenditure is positive and significant in all columns. However, we find the impact of R&D on the use of trade credit is mixed. More specifically, we find that the coefficient on R&D is positive and significant when using the Merton model and control for firm fixed effects, which is consistent with prior studies. On the other hand, the coefficient on R&D is negative and significant when using the Altman model and control for industry fixed effects. Generally, these results are consistent with the previous studies (e.g., Petersen and Rajan, 1997; Cuñat, 2007), that firms with high growth opportunities use more trade credit.

In addition, as expected, we find that ROA is negatively related to the use of trade credit and significant in all columns. These results align with those of Petersen and Rajan (1997), that profitable firms rely less on trade credit. Results also show that Cash Holding has a significantly positive coefficient in all columns, in line with Garcia-Appendini and Montoriol–Garriga (2013). Further, the impact of leverage on the use of trade credit is positive and significant in Columns (2) and (4). Although we expect leverage to be negatively correlated with the use of trade credit (as shown in Column

3), our findings may suggest that firms with high leverage are likely to be financially distressed and, thus, rely more on trade credit. Finally, the coefficient on Market Share is positive and significant across all columns, in line with Klapper et al. (2012), suggesting that firms with a high market share are likely to receive more trade credit from their suppliers.

Overall, the results in Table 2.3 are strongly consistent with our first hypothesis, “H1”, that firms facing financial distress use more trade credit. This finding is in line with Molina and Preve (2012), who find that firms in financial distress (measured by the coverage ratio) use more trade credit. Using market and accounting-based measures of financial distress, we provide a starting point that financially distressed firms rely more on trade credit financing. In the next subsection, we conduct robustness tests to check the reliability of our findings.

[Insert Table 2.3 here]

2.4.2 Robustness Tests

While our baseline results in Table 2.3 confirm the hypothesis that financially distressed firms increase their use of trade credit, we conduct a series of additional tests to determine the robustness of our baseline findings. Specifically, we first investigate whether our results are robust to alternative measures of the use of trade credit. Second, we examine to the extent to which our results are robust to alternative measures of financial distress. Third, we examine whether our results are robust to using principal component analysis, which combines financial distress measures into an aggregate measure. Fourth, we test whether our results are robust to alternative estimation methods (i.e., Fama-MacBeth estimates and two-way clustering). Finally, we investigate whether our results are robust to sub-period analyses.

2.4.2.1 Alternative Measures of Trade Credit

Our first sensitivity test uses an alternative definition of the use of trade credit, despite the fact that measuring the use of trade credit with the amounts of account payables to total assets is standard in the trade credit literature (e.g., Petersen and Rajan, 1997; Fisman and Love, 2003; Cuñat, 2007; Giannetti et al., 2011). However, other studies (e.g., Love et al., 2007) measure the use of trade credit with the amounts of accounts payable to cost of goods sold to capture fluctuations in the financing and economic activity (e.g., sales). Thus, we measure the use of trade credit in two alternative ways.

First, we scale accounts payable to the cost of goods sold, rather than total assets. Second, we scale accounts payable to total sales, rather than total assets.

Panel A of Table 2.4 presents the results when using alternative measures of trade credit. In Columns (1) and (2), the use of trade credit is measured as the ratio of accounts payable to cost of goods sold, while in Columns (3) and (4), the use of trade credit is measured as the ratio of accounts payable to total sales. Across all columns, the results show that our inferences remain unchanged. In particular, in Columns (1) and (3), when financial distress is measured using the Merton model, the coefficients on Distress_Merton are 0.0224 and 0.0243, respectively, which are statistically significant at the 1% level (t-statistics=3.12 and 6.05, respectively). Also, when using the Altman model (Columns 2 and 4), the coefficients on Distress_Altman are 0.0415 and 0.0320, respectively, and are statistically significant at the 1% level (t-statistics=5.72 and 10.06, respectively). Overall, these results confirm that our results are robust to alternative measures of trade credit.

2.4.2.2 Alternative Measures of Financial Distress

It is possible that the documented positive relation between financial distress and the use of trade credit may be driven by our choice of financial distress measures. To investigate this possibility, we consider two alternative measures of financial distress: the Ohlson (1980) O score and the Campbell et al. (2008) model. First, the Ohlson (1980) model is another accounting-based measure of financial distress, as in the Altman (1968) model. However, Ohlson (1980) criticises the method used by Altman (1968), i.e., multiple discriminant analysis (MDA), as it requires a matched sample that tends to be arbitrary and leads to misclassification of financial distress. Thus, Ohlson (1980) predicts financial distress by using conditional logit analysis (a static logit model) to avoid the problems associated with assumptions in the MDA method. The model consists of an intercept and nine accounting variables, including firm size, leverage, liquidity, profitability, and solvency. The outcome of this model indicates that a higher value of Ohlson O-score is associated with a higher level of financial distress.

The second alternative financial distress measure, the Campbell et al. (2008) model, is a "Hybrid" model based on market and accounting data. This model is estimated using a dynamic logit model. The model employs a set of market and accounting variables (and an intercept). The market variables used in this model are factors such as stock price, return volatility, excess return, and the firm's market equity relative to the S&P 500 index, while the accounting variables used are elements such as profitability, leverage and liquidity ratios. As in Ohlson (1980), a higher value of the Campbell et al. (2008) model is associated with a higher level of financial distress. We apply the same approach to our main financial distress measures and use the probability of default of both the Ohlson O-score and the Campbell et al. model. Since these models are estimated in a logit regression, we convert those measures into probabilities using the logistic cumulative distribution function.

Panel B of Table 2.4 presents the results for alternative measures of financial distress. In Column (1), financial distress is measured using the probability of default based on the Ohlson model, while in Column (2), financial distress is measured using the probability of default based on the Campbell et al. model. Using those two alternative measures, the results show that our inferences remain unchanged. Specifically, the results show that the coefficients on Distress_Ohlson and Distress_Campbell are 0.0355 and 0.0118, respectively, which are statistically significant at the 1% level (t-statistics=20.18 and 5.93, respectively). Collectively, the results in Panel B of Table 2.4 suggest that our results are robust to alternative measures of financial distress.

2.4.2.3 Financial Distress Measures Based on Principal Component Analysis (PCA)

Having shown that our results are robust to alternative measures of financial distress, we now attempt to reduce any error which may arise from the misidentification of financially distressed firms by constructing a comprehensive financial distress measure that is based on the common variation among the four measures of financial distress: 1) the Merton (1974) model, 2) the Altman (1968) model, 3) the Ohlson (1980) model, and 4) the Campbell et al. (2008) model. In particular, we use principal component analysis to combine the individual financial distress measures into an aggregate measure. This analysis helps us account for every aspect of financial distress and capture the systematic common component in one aggregate measure.

Panel C of Table 2.4 presents the results for principal component analysis. Panel C1 shows that our PCA yields one component with an eigenvalue greater than one (i.e., the eigenvalue is 2.3754) which can explain almost 59% of the total variance.[23] Also, Panel

[23] An eigenvalue greater than one suggests that the extracted component can explain more variance (Florackis and Sainani, 2018). In other words, it indicates that it has more explanatory power than any one of the original financial distress measures by itself.

C1 includes the factor loadings on each of the four financial distress measures for the first principal component (PC1). The results show that the weightings are evenly distributed across the four measures, and that each of them contributes relatively the same amount. In particular, the factor loadings for the four financial distress measures are, respectively, 0.4809 (Distress_Merton), 0.4899 (Distress_Altman), 0.5047 (Distress_Ohlson), and 0.5234 (Distress_Campbell). A greater value for the factor indicates a better aggregate financial distress measure. In Panel C2, we use these loadings to extract the common factor and examine its correlation with the four financial distress measures. As expected, PC1 is positively correlated with all financial distress measures, with the correlation being greater than 0.74 in all cases. Specifically, PC1 has correlation coefficients of 0.74 with Distress_Merton, 0.75 with Distress_Altman, 0.77 with Distress_Ohlson, and 0.80 with Distress_Campbell. Further, Panel C2 presents the correlation matrix among financial distress measures. Generally, the high correlations among the four measures of financial distress justify the use of PCA for constructing the aggregate measure of financial distress.

Finally, in Panel C3, we re-examine our baseline model by rerunning our regressions with the first principal component (PC1) substituting for individual financial distress measures. We include the same control variables as Table 2.3, but not reported for brevity. We find that the coefficient on PC1 is positive (0.0036) and significant at the 1% level (t-statistic=12.56). Thus, our results are robust to using principal competent analysis to construct a comprehensive financial distress measure based on the four measures of financial distress.

2.4.2.4 Alternative Estimation Methods

In our baseline model, we use robust standard errors to account for heteroscedasticity and autocorrelations in the residuals of the pooled OLS regression. For robustness, we further address the concern that our baseline model may be sensitive to alternative model specifications. First, we re-estimate our results using the regression of Fama and MacBeth (1973) to account for any cross-correlations and the serial correlations in the residual terms. In particular, we estimate cross-sectional regressions of financial distress on the use of trade credit for each year separately, controlling for industry fixed effects. We then average the yearly cross-sectional slope coefficients to obtain the final estimates, and the time series of the coefficient estimates are used to estimate standard errors.

Panel D of Table 2.4 presents results for alternative estimation methods. All regressions have the same control variables as in Table 2.3 (not tabulated). **Estimation (1)** in Panel D of Table 2.4 presents the Fama-MacBeth estimates. In Column (1), we use the Merton model measure of financial distress, while in Column (2), we use the Altman model. In both columns, the results show that the coefficients on Distress_Merton and Distress_Altman are significantly positive. Specifically, the coefficient estimate on Distress_Merton is 0.0373 and significant at the 1% (t-statistic=7.67) and the coefficient estimate on Distress_Altman is 0.0545 and significant at the 1% (t-statistic=11.54).

We further re-estimate our baseline model using Petersen's (2009) two-way clustering methodology that simultaneously controls for cross-sectional and time-series dependencies. We first use two-clustering at firm and year in **Estimation (2)** in Panel D of Table 2.4. We also use two-clustering at industry and year in **Estimation (3)** in Panel D of Table 2.4. In both estimations, the results show that the coefficient estimates on Distress_Merton and Distress_Altman are significantly positive. Overall, our results remain similar when we re-estimate our baseline model using both Fama and MacBeth's (1973) regression and Petersen's (2009) two-way clustering.

2.4.2.5 Sub-Periods Analysis

Finally, to test the robustness of our baseline results over time, we regress our baseline model over different sub-periods. Since we use a relatively long sample period (i.e., 1976–2017), it is interesting to examine whether the documented positive relation between financial distress and the use of trade credit holds over time. Panel E of Table 2.4 presents results for sub-periods. In particular, we use 1976–1986 as **Period 1**, 1987–1997as **Period** 2, 1998–2008 as **Period 3** , and 2009–2017 as **Period 4**. We use the same control variables as those used in Table 2.3. In Column (1), we report the results when financial distress is measured using the Merton model. In Column (2), the results are reported when financial distress is measured using the Altman model. In Column (1), the results show that the coefficient on Distress_Merton is positive and significant in all sub-periods, except for the earliest sub-period ranging between 1976 and 1987. One possible explanation for the disappearance of the explanatory power of financial distress in the early few years of the study period is that the level of financial distress during 1976-1986 is lower than the other periods.[24] However, the results when we use the Altman model in Column (2) show that the documented positive impact of financial distress on the use of trade credit is significant in all sub-periods.[25] Generally, the results in Panel E of Table 2.4 suggest that the positive impact of financial distress on the use of trade credit holds over time, particularly after the earlier years.

[Insert Table 2.4 here]

2.4.3 Addressing Potential Endogeneity

Thus far, our results (Table 2.3 and Table 2.4) yield robust results and support the hypothesised effects of financial distress. However, the relation between financial distress and the use of trade documented in our baseline regression is potentially endogenous. While the inclusion of firm fixed effects helps mitigate concerns regarding time-invariant omitted variables, there may be some unobserved variable that varies across time and drives both trade credit and financial distress. In addition, it is possible that firms self-select themselves to get into distress/bankruptcy. Previous studies (e.g., Bris et al., 2005; Stromberg, 2000; Thorburn, 2000) show that firm characteristics have important influences on firms' decisions to enter into distress/bankruptcy. Further, reverse causality between the use of trade credit and financial distress is another concern; it may be that increases in the use of trade credit prompt the level of financial distress. Prior research (e.g., Altman, 1984; Opler and Titman, 1994; Andrade and Kaplan, 1998) finds a significant increase in financial distress when the firm significantly increases its use of trade credit as a source of financing. Given that trade credit is an expensive source of financing (Ng et al., 1999; Wilner, 2000), it is not surprising that the use of trade credit increases the level of financial distress. We attempt to address these endogeneity concerns using (1) Propensity score matching analysis (PSM), (2) High-dimensional fixed effects, (3) the Instrumental variable approach, (4)

[24] In untabulated analysis, we find that the mean of Distress_Merton is 0.0174 during the period 1976-1987. However, we find that the mean of Distress_Merton is 0.0262 and 0.0256, over the period 1987-1997 and 1998-2008, respectively. These two periods witnessed several financial crises (e.g., Asian financial crisis, the collapse of the dotcom bubble and the global financial crisis), which likely resulted in increasing financial distress.

[25] The documented relation between financial distress and the use of trade credit is significant during 1976-1987 only at the 10% level. Also, in untabulated tests, we find that the mean of Distress_Altman is 0.0584 during the period 1976-1987 and it is 0.0768 and 0.1112, over the period 1987-1997 and 1998-2008, respectively. These findings support our suspicion that financial distress in the early years of the study period is lower than in the other periods.

the Difference-in-Differences approach, and (5) the triple Difference-in-Differences approach.

2.4.3.1 Propensity Score Matching Estimates

As a first step to alleviate endogeneity concerns, we employ a propensity score matching (PSM) approach whereby, financially distressed firms are matched with financially non-distressed firms. Our main results could be driven by the differences in firms' fundamentals between the distressed and non-distressed firms (Dehejia and Wahba, 2002). In particular, firms may self-select themselves to go into distress, and such a choice may be driven by firms' characteristics that also affect their use of trade credit. For example, if distressed firms are smaller and younger than non-distressed firms, then these characteristics could drive our results.

To form our matched sample, we first run a logistic regression that estimates the probability of being a distressed firm, based on firm size, firm age, industry, and year. We classify firms as distressed or non-distressed based on the two measures of financial distress: the Merton model and the Altman model. For the Merton model (i.e., Distressed1), we classify a firm as distressed if firm-year observations are in the top quartile of the Distress_Merton distribution, and zero otherwise. For the Altman model (i.e., Distressed2), we classify firms as distressed if the firm's Altman Z score is below 1.81, and zero otherwise. We then implement one-to-one propensity score matching without replacement. We require the propensity score distance between each matched pair to be within 1% (i.e., a caliper of 0.01). Then, we re-run our main baseline regression on the propensity score matched samples.

Table 2.5 presents the results for the propensity score matching estimates. In Columns (1) and (3) (Pre-match) of Panel A, we report the estimation results for the logistic model used to estimate the propensity scores. In both columns, whether using the Merton model or the Altman model, the results suggest that distressed firms are smaller and younger than non-distressed firms. Specifically, the results in Columns (1) and (3) show respectively that Distressed1 and Distressed2 are significantly negatively associated with firm size and firm age. The fitted values (propensity scores) in Columns (1) and (3) are then used to match the distressed firms with non-distressed firms.

We conduct three diagnostic tests to verify that the observations in the distressed and non-distressed groups are sufficiently indistinguishable in terms of observable characteristics. The first test involves re-estimating the logit model using the matched sample. The results are reported in Columns (2) and (4) in Panel A of Table 2.5. None of the coefficient estimates (i.e., firm size and firm age) is statistically significant, indicating no distinguishable trends between the distressed and non-distressed groups. Further, the coefficients in Columns (2) and (4) are smaller in magnitude than those in Columns (1) and (3), indicating that the results are not merely an artefact of a decline in the number of degrees of freedom in the restricted sample. In addition, the overall explanatory power (represented by the pseudo R^2) decreases from 0.0951 (0.1575) in the pre-match sample to only 0.0021 (0.0038) in the post-match sample, indicating that firm characteristics do not explain any variation in whether a firm is distressed or non-distressed.

The second test examines the difference between the propensity scores of distressed firms and non-distressed firms and tabulated in Panel B of Table 2.5. In both measures (Distressed1 and Distressed2), the results show that there is no difference in the propensity score between distressed firm-year observations and non-distressed firm-year observations. The third test investigates the difference in means (balancing test) for firm size and age between the distressed and non-distressed groups after matching. The results are reported in Panel C of Table 2.5. Columns (1) through (3) present the results for the Merton model of financial distress (i.e., Distressed1), while Columns (4) through (6) present the results for the Altman model of financial distress (i.e., Distressed2). In both measures, the results show that none of the differences is statistically significant, which confirms the findings in Panels A and B. Overall, the diagnostic test results appear to suggest that the matching is satisfactory.

In addition, Panel C of Table 2.5 shows that, in the matched sample, the use of trade credit is greater for distressed firms than non-distressed firms. Specifically, distressed firms have a mean trade credit of 11.37% based on Distressed1 (9.48% based on Distressed2), while non-distressed firms have a mean trade credit of 9.35% based on Distressed1 (8.06% based on Distressed2). The difference between the trade credit ratios of the two groups is statistically significant. Finally, in Panel D of Table 2.5, we re-estimate the baseline regression model using the matched samples. We use the same control variables used in Table 2.3. In Column (1), financial distress is measured using the Merton model (i.e., Distressed2), while in Column (2), financial distress is measured using the Altman model (i.e., Distressed2). In both columns, the results confirm that financial distress has a positive impact on the use of trade credit. This impact is significant at the 1% level in both columns (t-statistics=4.86 and 4.85, respectively).

Overall, the results in Table 2.5 suggest that the observed positive impact of financial distress on the use of trade credit is not driven by observable differences in firm characteristics.

[Insert Table 2.5 here]

2.4.3.2 High-Dimensional Fixed Effects

Although our PSM analysis mitigated the concern that the use of trade credit is driven by observable differences in firm characteristics, it has one weakness in that it only controls for observed firm characteristics. The relationship between financial distress and the use of trade credit might also be subject to unobservable within-group heterogeneity. For instance, trade credit and financial distress might be subject to time-varying heterogeneity across industries, such as industry-wide shocks to credit supply. To address this concern, we follow Gormley and Matsa (2014) and include multiple high-dimensional fixed effects in our baseline regression. In particular, we add both firm fixed effects and industry-by-year fixed effects into Equation 2.1. Moreover, the relationship between financial distress and the use of trade credit is likely to be confounded by any time-varying state characteristics (e.g., geographic location and local economic conditions). To address this concern, we further control for unobserved economic trends in the firm's state that might confound the results by including state-by-year fixed effects in our baseline model.

Table 2.6 presents the results for high-dimensional fixed effects. Columns (1) through (2) present the results when financial distress is measured using the Merton model, while Columns (3) through (4) present the results when financial distress is measured using the Altman model. In Columns (1) and (3), we include industry-year fixed effects rather than only firm fixed effects. In Columns (2) and (4), in addition to industry-year fixed effects, we include state-year fixed effects. In all columns, the results are similar to the specification in Table 2.3 that controls for firm and year fixed effects. Specifically, the coefficient on Distress_Merton is 0.0205 and is significant at the 1% level (t-statistic=5.11) when we control for industry-year fixed effects, while it is 0.0213 and significant at the 1% level (t-statistic=5.21) when we control for industry-year fixed effects and state-year fixed effects. Further, the coefficient on Distress_Altman is 0.0213 and is significant at the 1% level (t-statistic=7.54) when we control for industry-year fixed effects, and it is also 0.0213 and significant at the 1% level (t-statistic=7.41)a when we control for industry-year fixed effects and state-year fixed effects. Overall, the results in Table 2.6 provide further support that financial distress has a positive impact on the use of trade credit after controlling for unobserved firm characteristics.

[Insert Table 2.6 here]

2.4.3.3 Instrumental Variable Approach

A potential source of endogeneity is that there might be a common omitted factor that drives both financial distress and the use of trade credit, which would bias the coefficient of financial distress measures. While financial distress and the use of trade credit might be unrelated, they might be both correlated to a variable that is not included in our baseline model (Equation 2.1). We address this potential endogeneity issue by conducting an instrumental variable approach. The ideal instrument should be directly correlated with financial distress, but is unlikely to have any correlation with the use of trade credit. In the spirit of Alfaro et al. (2018), we use aggregate volatility shocks in currency, policy, and treasuries as instrumental variables of financial distress. In particular, we address endogeneity concerns about financial distress by instrumenting with industry-level non-directional exposure to nine different sources of uncertainty shocks: seven widely traded currencies[26], U.S. 10-year treasuries and a policy uncertainty index (from Baker et al., 2016). Alfaro et al. (2018) argue that these aggregate volatility shocks have an exogenous effect on firm-level volatility, and that they are orthogonal to the endogenous components driving firm-level volatility shocks. In support of this effect, Alfaro et al. (2018) document that each of these sources of aggregate uncertainty shocks is positively correlated with firm-level volatility shocks. We believe that, given that these aggregate volatility shocks affect firm-level volatility, firm-level financial distress will be driven by these instruments. This is especially true when we use market-based measures of financial distress because they are heavily dependent on firm-level volatility to predict financial distress. Accordingly, these aggregate volatility shocks could satisfy both the inclusion restriction (i.e., correlated with financial distress measures) and the exclusion restriction (i.e., not directly correlated with the use of trade credit other than through financial distress measures).

To conduct this analysis, we undertake a two-stage least squares (2SLS) regression in which we first regress financial distress measures on the instrumental variables (i.e.,

[26] These currencies include the Australian Dollar (AUD), Canadian Dollar (CAD), Euro, Swiss Franc (CHF), British Pound (GBP), Japanese Yen (JPY), and Swedish Krona (SEK).

Vol Exposure Aud, Vol Exposure Cad, Vol Exposure Euro, Vol Exposure Chf, Vol Exposure Gbp, Vol Exposure Jpy, Vol Exposure Sek, Vol Exposure Policy, Vol Expos Treasury), and then the use of trade credit is regressed on the predicted financial distress measures of the first stage. In this way, the coefficient in the second stage captures the effect on the use of trade credit of the exogenous variation in financial distress.

Table 2.7 presents the results. Columns (1) through (2) present the results when financial distress is measured using the Merton model, while Columns (3) through (4) present the results when financial distress is measured using the Altman model. Column (1) of Table 2.7 presents the first-stage regression results with Distress_Merton as the dependent variable to check the relevance of the instruments. The explanatory variables include the above-mentioned nine instruments[27] and the changes in the price of each of the nine aggregate instruments (i.e., first-moment return shocks) as controls in the model.[28] Moreover, we use the same set of controls as in the baseline models in Table 2.3. Consistent with the rationale behind the instruments, the results in Column (1) of Table 2.7 show that Distress_Merton is positively correlated to most of our instruments. In particular, Distress_Merton is significantly positively correlated to Vol Exposure Aud, Vol Exposure Chf, Vol Exposure Euro, Vol Exposure Gbp, Vol Exposure Jpy, Vol Exposure Policy, and Vol Expos Treasury, while it is not significantly correlated to Vol Exposure Cad and Vol Exposure Sek. Moreover, we see that the F-statistic indicates a well-identified first stage, with a respective value of 12.148 for the Cragg-Donald (CD) F-statistic (i.e., Cragg-Donald F-test exceeds Staiger and Stock (1997) thresholds). The F-statistic of the first-stage regression also passes the Stock and Yogo (2005) relative bias and relative size tests. This means that our instruments succeed in identifying the exogenous variation in financial distress that arises from different unrelated sources of aggregate uncertainty shocks. Further, we also find that the P-value (0.2541) for Hansen's (1982) J over-identification does not reject the validity of our instruments. Hence, we cannot reject the null that our instruments are exogenous. Accordingly, both the inclusion and exclusion restrictions for our instruments are satisfied.

Column (2) of Table 2.7 presents the second stage regressions results, where the dependent variable is the use of trade credit. The variable of interest is the variable with

[27] The data are obtained from https://sites.google.com/a/umn.edu/xiaojilin/working-papers. The data is available over the period 1996-2016.

[28] Following Alfaro et al.(2018), we use the first moment of the instruments as controls to disentangle the impact of second moment uncertainty shocks from first moment aggregate.

the predicted values of financial distress measure (i.e., Instrumented_Distress_Merton) from the first-stage regressions. The coefficient estimates on Instrumented_Distress_Merton is positive and significant at the 5% level (t-statistic=2.28), confirming the positive effect of financial distress on the use of trade credit. Moreover, Column (3) of Table 2.7 presents the results of the first stage regressions in which the dependent variable is Distress_Altman. The results show that Distress_Altman is positively correlated to Vol Exposure Cad and Vol Exposure Sek. However, Distress_Altman is not significantly correlated to the remaining instruments. Moreover, although the Cragg-Donald (CD) F-statistic accepts the hypothesis of weak IV (i.e., CD F-statistics of 1.822), the P-value (0.2406) for Hansen's (1982) J over-identification accepts the validity of our instruments. Thus, we cannot reject the null that our instruments are valid. Also, the results for the second stage regressions for the Altman model in Column (4) of Table 2.7 show that the coefficient estimate on Instrumented_Distress_Altman is positive and significant at the 10% level (t-statistic=1.77), confirming the positive effect of financial distress on the use of trade credit.

In addition, we observe that, in both measures of financial distress, the magnitude of the 2SLS coefficient estimates capture a much more positive relationship between financial distress and the use of trade credit than that reported in Table 2.3, suggesting a potential downward bias in our baseline results. Overall, the results from the instrumental variable approach analysis further support the view that the positive impact of financial distress on the use of trade credit is not due to endogeneity in financial distress measures.

[Insert Table 2.7 here]

2.4.3.4 Difference-in-Differences (DiD): Evidence from the 2007-2008 Financial Crisis

As mentioned previously, the relation between financial distress and the use of trade credit might be subject to reverse causality concerns. To establish causality, we adopt a difference-in-differences approach using the 2007-2008 financial crisis as an exogenous shock to firms' financial distress and examine whether and how the increase in financial distress following the crisis affects the use of trade credit. The 2007-2008 global financial crisis provides a good setting to investigate the relationship between financial distress and the use of trade credit. The aftermath of the 2007-2008 financial crisis resulted in widespread financial distress of non-financial firms (International Monetary Fund (IMF), 2012). This suggests that financial crises are expected to increase a firm's financial distress, as documented by early work on the issue (e.g., Altman, 1973; Mensah, 1984); financial distress increases during financial crises due to tight financial conditions that make it difficult for firms to meet debt obligations. This situation allows us to examine how the use of trade credit responded to this increased financial distress during the financial crisis, thus providing a natural experimental research setting and avoiding the endogeneity concern. Further, because the 2007-2008 financial crisis is a dramatic event with severe consequences for various firms and countries worldwide (Rudolph and Schwetzler, 2013), this event is unlikely to have been caused by firms' use of trade credit, ruling out concerns that reverse causality exists.

In our difference-in-differences analysis, we focus on firms that entered the crisis with high leverage and low interest coverage as an exogenous shock to financial distress. Previous studies (e.g., Cantor, 1990; Lang and Stulz, 1992; Opler and Titman, 1994; Bougheas et al., 2006) suggest that firms that maintain a high level of leverage tend to experience more difficulties during economic downturns. Further, they argue that during a crisis, capital providers are likely to be more risk-averse and reluctant to lend or invest.[29] Thus, highly-leveraged firms and firms with low interest coverage are likely to have limited access to sources of financing. Accordingly, we expect such firms to increase their use of trade credit after the 2007-2008 financial crisis.

To conduct this analysis, we focus on the year before (i.e., 2007) and the year after (i.e., 2008) the financial crisis, namely, the year before of the crisis and the year after the crisis. A short window is used for this analysis to avoid possible confounding events that might result from a longer time period. Thus, we construct an indicator variable, After_Crisis, which takes a value of one for the fiscal year 2008 and zero for the fiscal year 2007. Then, we construct a sample of treatment and control firms based on high leveraged firms and firms with low interest coverage. For high leveraged firms, we construct an indicator variable, Treat_(High_Leverage), which takes a value of one for firms in the top quartile of leverage ratio distribution during one year before the crisis (e.g., the year 2007). For interest coverage, we construct an indicator variable, Treat_(Low_Interest_Cov), which takes a value of one for firms in the bottom quartile

[29] Prior research argues that the 2007-2008 financial crisis leads to a severe shock to the supply of external finance (e.g., Duchin et al., 2010; Almeida et al., 2011; Garcia-Appendini and Montoriol-Garriga, 2013).

of interest coverage ratio distribution during one year before the crisis . We also use another indicator, Treat_(Interest_Cov_Below_One), to capture the firms with low interest coverage at the beginning of the crisis. In particular, we follow Asquith et al.(1994) and define firms with low interest coverage if their interest coverage ratio is less than one during one year before the crisis . We then add the interaction term between the three indicators mentioned above and After_Crisis into Equation 2.1 instead of financial distress measures, creating a difference-in-differences (DiD) estimator. In particular, we perform a difference-in-differences estimation by analysing the following model:

$$AP/TA_{it+1} = \beta_0 + \beta_1 Treated_{it} + \beta_2 After_{Crisis_{it}} + \beta_3 Treated \times After_{Crisis_{it}} + \theta X_{it} + \varepsilon_{it} \qquad \text{Eq. 2.2}$$

Where Treated is a dummy variable that can be either: Treat_(High_Leverage), Treat_(Low_Interest_Cov), or Treat_(Interest_Cov_Below_One). After_Crisis is a dummy variable equal to one in the period after the crisis, and zero otherwise. The coefficient of interest in Equation 2.2 is Treated × After_Crisis, which captures the difference-in-differences effect, meaning the use of trade credit for firms with high leverage or low interest coverage during one year before the crisis. We expect the coefficient on Treated × After_Crisis will be positive and statistically significant.[30]

Table 2.8 presents the results. In Column (1), the treatment group comprises firms that maintain a high level of leverage during one year before the crisis (i.e., based on the top quartile of leverage ratio distribution). In Column (2), the treatment group comprises firms in the bottom quartile of interest coverage distribution during one year before the crisis. In Column (3), the treatment group includes firms that have an interest coverage ratio below during one year before the crisis. Across all columns, the results show that the treatment firms experience an increase in the use of trade credit after the crisis, relative to the control firms. In particular, the results in Column (1) show that the coefficient on Treat_(High_Leverage) × After_Crisis is 0.003 and is statistically significant at the 5% level (t-statistic=2.00). In Column (2), the coefficient on Treat_(Low_Interest_Cov) × After_Crisis is 0.0059 and is statistically significant at the 1% level (t-statistic=2.89). Finally, in Column (3), the coefficient on Treat_(Interest_Cov_Below_One) × After_Crisis is 0.0099 and is statistically significant at the 1% level (t-statistic=3.37). Overall, the DiD analysis results

[30] Note that Treat_(High_Leverage), Treat_(Low_Interest_Cov), and Treat_(Interest_Cov_Below_One) are dropped from the regression because they are subsumed by firm fixed effects.

documented in Table 2.8 suggest a causal relation between financial distress and the use of trade credit and further mitigate the concerns about reverse causality and other potential endogeneity issues.

[Insert Table 2.8 here]

2.4.3.5 Triple Difference-in-Differences (DiDiD): Evidence from Hurricane Strikes

We further establish the causality of financial distress on the use of trade credit using natural disasters as an exogenous shock to financial distress. Specifically, in the spirit of Aretz et al. (2019), we explore a quasi-natural experiment, a hurricane strike, and use this natural disaster with multiple periods to study whether the use of trade credit increases in response to financial distress increases brought about by hurricane strikes. There are several reasons why a hurricane strike is an ideal setting to study the impact of financial distress on the use of trade credit. First, the inclusion restriction, that hurricane strikes meaningfully affect the financial distress of firms located in the hit regions, could be fulfilled. Specifically, hurricane strikes cause significant economic damage (Aretz et al., 2019). For instance, Pielke et al. (2008) and Blake et al. (2011) show that Hurricane Katrina resulted in estimated property damage of $113 billion. Further, Hsiang and Jian (2014) find that hurricane strikes resulted in a long-run decline in economic growth.

Second, the effects of hurricane strikes extend over many U.S. regions, which mitigate the concern that firms relocate away from hurricane affected regions and, thereby, ensure that firms are randomly assigned to treatment. Blake et al. (2011) show that hurricane strikes not only damage coastal areas, but also damage inland areas. Further, they show that hurricane strikes usually cause flooding because of the torrential rain associated with hurricane strikes. Thus, most firms are exposed to hurricane strikes (Dailey et al., 2009). Third, hurricane strikes incidences and paths are almost impossible to predict, ruling out the concern that firms react to hurricane strikes before they happen (Emanuel and Zhang, 2016). According to The National Centre for Atmospheric Research (NCAR), hurricane strikes incidences are difficult to forecast because a potential hurricane might be either nurtured or deflated by minor variations in the atmosphere.

However, the exclusion restriction that hurricane strikes must affect a firm's use of trade credit only through increasing financial distress may be violated. Hurricane strikes could affect the use of trade credit through other channels. For example, a hurricane strike could affect a firm's product markets, labour markets, and growth opportunities (Aretz et al., 2019). Thus, hurricane strikes are anticipated to lead managers to rethink the firm's business model and financing decisions, and to spur changes in the use of trade credit for non-distress reasons. Accordingly, we follow the methodology of Aretz et al. (2019) and conduct triple difference-in-difference (DiDiD) to examine the effects of hurricane strikes on the use of trade credit through increasing financial distress. In particular, we first compare hurricane-struck firms with non-hurricane-struck firms. We then compare pre-hurricane-strike non-distressed firms with pre-hurricane-strike distressed firms. This methodology (DiDiD) helps us differentiate the effects of hurricane strikes through non-distress channels, mitigating the concern that our tests violate the exclusion restriction. More specifically, we perform a triple difference-in-differences estimation by analysing the following model:

$$AP/TA_{it} = \beta_0 + \beta_1 Treat(Hurricane)_{it} + \beta_2 Distressed_{it} + \beta_3 After\_Hurricane_{it} + \beta_4 Treat(Hurricane)_{it} \times After\_Hurricane_{it} + \beta_5 Treat(Hurricane)_{it} \times Distressed_{it} + \beta_6 Distressed_{it} \times After\_Hurricane_{it} + \beta_7 Treat(Hurricane)_{it} \times Distressed_{it} \times After\_Hurricane_{it} + \theta X_{it} + \varepsilon_{it} \quad \text{Eq. 2.3}$$

Where Treat_(Hurricane) is an indicator variable equal to one for firm-year observations associated with firms located in a hurricane-struck county over the 6 year-period surrounding a hurricane strike, and zero otherwise. To identify these hurricane-struck counties, we use data from the Spatial Hazard and Event Losses Database for the U.S. (SHELDUS). We use the major hurricane strikes according to total damages (adjusted for inflation) that occurred over the 1979–2011 period. We further ensure that there is a gap of at least 6 years between the hurricane strikes. This gap helps us avoid overlap between the earlier hurricane's post-event period and the later hurricane's pre-event period. Thus, we use six periods that include major hurricane strikes, namely, hurricane strikes that occurred in: 1979, 1985, 1991, 1998, 2005, and 2011.[31]

Accordingly, the variable After_Hurricane in Equation 2.3 is an indicator variable equal to one for the 3 years after a hurricane strike, and zero otherwise. Distressed is defined as an indicator variable equal to one if the firm is financially distressed one year before the hurricane strike. We use both the Merton and Altman models measures of

[31] These include, for example, Atlantic hurricane seasons, Pacific hurricane seasons, Hurricane Bob, Hurricane David, Hurricane Danny, Hurricane Gloria, Hurricane Bonnie, Hurricane George, Hurricane Mitch, Hurricane Katrina, Hurricane Rita, and Hurricane Irene.

financial distress. For Distress_Merton, we construct an indicator variable equal to one for firms in the top quartile of the Distress-Merton distribution (during one year before the hurricane strike). For Distress_Altman, we construct an indicator variable equal to one if the firm's Altman Z score is below 1.81 (one year before the hurricane strike), and zero otherwise. The coefficient of interest in Equation 2.3 is Treat_(Hurricane) × Distressed × After_Hurricane, which captures the triple difference-in-differences effect. We expect the coefficient on Treat_(Hurricane) × Distressed × After_Hurricane to be positive and statistically significant.

Table 2.9 presents the results for triple difference-in-difference featuring control variables and firm- and year fixed effects. In Column (1), financial distress is measured by the Merton model. The table shows that the coefficient on Treat_(Hurricane) × Distress_Merton × After_Hurricane is positive and significant at the 5% level (t-statistic=2.02). On the other hand, the results show that the coefficient on Treat_(Hurricane) × After_Hurricane is insignificant. Similarly, in Column (2), when we use the Altman model, the coefficient on Treat_(Hurricane) × Distress_Altman × After_Hurricane is positive and significant at the 10% level (t-statistic=1.66), while the coefficient on Treat_(Hurricane) × After_Hurricane is insignificant. Collectively, the results indicate that the impact of hurricane strikes on the use of trade credit is more pronounced for pre-hurricane-strike distressed firms.

Further, we estimate additional specifications to examine the robustness of our results in Columns (1) and (2) of Table 2.9. First, to mitigate the indirect effects of hurricane strikes, we exclude from the control group sample those associated with firms located within 50 miles of each struck county.[32] The results are reported in Columns (3) and 4 of Table 2.9. The results remain qualitatively unchanged when excluding such firms. As a final robustness check, we use a matched sample in which hurricane-struck firms are matched with non-hurricane-struck firms based on one-to-one propensity score matching. Propensity scores are obtained from a logit regression of a dummy variable equal to one for observations associated with the hurricane-struck firms (during one year before hurricane strike) on a set of matching variables, including firm size, firm age, tangibility, market-to-book ratio, leverage, R&D, ROA, sales growth, cash holding, market share and industry dummies. Again, the results hold after controlling

[32] The distance between counties data (in miles) is obtained from the National Bureau of Economic Research database, which is available at : https://www.nber.org/research/data/county-distance-database.

for underlying differences between hurricane-struck firms and non-hurricane-struck firms.

In summary, the results reported in Table 2.9 suggest that firms are likely to use more trade credit in response to exogenous financial distress increases induced through hurricane strikes. Thus, using hurricane strikes as an exogenous shock to financial distress, we establish a causal relationship between financial distress and the use of trade credit and further mitigate the concerns that this relationship is endogenous.

[Insert Table 2.9 here]

2.4.4 Cross Sectional Analysis

Our empirical results have thus far provided consistent evidence that financial distress positively affects the use of trade credit financing. The results support the notion that distressed firms are expected to use more trade credit to substitute for alternative sources of financing. Distressed firms are likely to have limited access to alternative sources of financing because their capital providers are expected to be less willing to extend additional financing, due to the risk of default. However, suppliers are likely to be more inclined to work as liquidity providers to these firms, because they are in a better position than capital providers to assess their customers' credit risk and enforce debt repayment in the case of default. To further understand whether distressed firms use more trade credit because they have limited access to alternative sources of financing and because their suppliers have financing advantages over traditional financial institutions, in this sub-section, we investigate this relationship in the cross-section. Specifically, we investigate whether the impact of financial distress on the use of trade credit varies with: (1) information opacity, and (2) social trust. To conduct the analyses, we rerun regressions based on Equation 2.1 and further include interaction terms to capture the cross-sectional differences in the effects of financial distress on the use of trade credit.

2.4.4.1 Information Opacity

Our first cross-sectional test examines whether the impact of financial distress on the use of trade credit varies with the level of the firm’s information opacity. The second hypothesis, “H2”, implies that the positive impact of financial distress on the use of trade credit is greater for firms with a more opaque information environment. To test this hypothesis, we use two proxies for information opacity: (1) the number of analysts following the firm and (2) the probability of informed trading (PIN). Prior research shows that financial analysts following the firm play an important role in monitoring the firm's performance (e.g., Brennan and Subrahmanyam, 1995; Hong et al., 2000; Das et al., 2006; Mola et al., 2013). Financial analysts are likely to have greater monitoring power and, hence, the information produced by financial analysts is expected to help capital market participants analyse the firm's stock price, stock liquidity valuation, investments and financing decisions (e.g., D'Mello and Ferris, 2000; Bradley et al., 2003; Chang et al., 2006; Derrien and Kecskes, 2013; Kim et al., 2019). This means that analyst coverage plays an important role in reducing the firm's information opacity or asymmetry. Thus, firms followed by fewer analysts are expected to have higher information asymmetry or opacity (Lang and Lundholm, 1993; Kelly and Ljungqvist, 2012). To identify firms with high information opacity because of their number of analysts, we construct an indicator variable, Low Analysts, which takes a value of one for firms in the bottom quartile of the number of analysts following the firm distribution in a given year, and zero otherwise.

The second proxy for information opacity, the probability of informed trading, addresses the adverse selection problem when the trade is based on private information held by privately informed investors of the firm (Brown and Hillegeist, 2007). A higher probability of informed trading indicates a greater amount of private information reflected in a stock price (Easley et al., 1996; Duarte and Young, 2009). This means that a high probability of informed trading (PIN) is associated with a high level of information asymmetry or opacity. To identify firms with high information opacity because of their high PIN, we construct an indicator variable, High PIN, which takes a value of one for firms in the top quartile of the probability of informed trading distribution in a given year, and zero otherwise.

We then add the interaction term between financial distress measures (e.g., Distress_Merton and Distress_Altman) and information opacity measures (e.g., Low Analysts and High PIN) to Equation 2.1. In this test, the coefficient on Distress_Merton (Distress_Altman) captures the impact of financial distress on the use of trade credit for firms with low information opacity, and the coefficient on Distress_Merton (Distress_Altman) × Low Analysts (High PIN) captures the effect of financial distress on the use of trade credit for firms with high information opacity relative to those with low information opacity. The variable of interest is Distress_Merton (Distress_Altman) × Low Analysts (High PIN). According to our second hypothesis, we expect the coefficient on Distress_Merton (Distress_Altman) × Low Analysts (High PIN) to be positive and significant.

Table 2.10 presents the results for the heterogeneous effect of financial distress on the use of trade credit and show that it varies predictably with the level of information opacity. In Columns (1) and (3), information opacity is proxied by the number of analysts, while in Columns (2) and (4), information opacity is proxied by the probability of informed trading (PIN). In Columns (1) and (2), financial distress is measured using the Merton model, while in Columns (3) and (4), financial distress is measured using the Altman model. The table shows that the coefficient on Distress_Merton × Low Analysts is positive and significant at the 1% level (t-statistic=4.60). To get an idea of the magnitude of our results in Column (1), our results suggest that, for firms followed by many analysts (i.e., Low Analyst = 0), the marginal effect of financial distress on trade credit is equal to 0.025. However, for firms followed by fewer analysts (i.e., Low Analyst = 1), the marginal effect goes up to 0.0325 (= 0.0025+ 0.0300). In terms of economic magnitude, the coefficient estimate in Column (1) suggests that, compared to firms followed by a large number of analysts, a one standard deviation increase in the probability of default (Distress_Merton) leads to an increase in the use of trade credit by about 0.24 percentage points (0.0734 × (0.0025+ 0.0300)) for firms followed by a fewer number of analysts. This magnitude is 2.52% (3.24%) of the mean (median) accounts payable to total assets per standard deviation increase in the probability of default based on the Merton model.

Likewise, the results when using the Altman model (Column 3 of Table 2.10) show that the coefficient on Distress_Altman × Low Analysts is positive and significant at the 1% level (t-statistic=4.36). Our results in Column (3) suggest that for firms followed by many analysts (i.e., Low Analyst = 0), the marginal effect of financial distress on trade credit is equal to 0.0116, while for firms followed by fewer analysts (i.e., Low Analyst = 1), the marginal effect is 0.0273 (= 0.0116+ 0.0157). Economically, the coefficient estimate in Column (3) suggests that a one standard deviation increase in the probability of default (Distress_Altman) increases the use of trade credit by approximately 0.48 percentage points (0.1761 × (0.0116+ 0.0157)) for firms followed by a fewer number of analysts. This magnitude is 5.07% (6.53%) of the mean (median) accounts payable to total assets per standard deviation increase in the probability of default based on the Altman Model.

Moreover, the coefficient on Low Analysts in Columns (1) and (3) captures how, and whether, firms with high information asymmetry, due to a low number of analysts, use more trade credit. Consistent with previous studies (Petersen and Rajan, 1997; Chemmanur and Toscano, 2019), our results show that firms having high information opacity, based on their number of analysts, rely more on trade credit. In particular, the coefficient on Low Analysts is positive and significant at the 1% level in both Columns (1) and (3) (t-statistics=4.94 and 3.76, respectively). Overall, the results in Columns (1) and (3) suggest that firms that face financial distress, and which are followed by fewer analysts, use more trade credit than those firms facing financial distress that are followed by a large number of analysts. Thus, the results suggest that the positive impact of financial distress on trade credit is more (less) important for firms with high (low) information opacity.

In addition, Columns (2) and (4) of Table 2.10 present the results when information opacity is proxied by the probability of informed trading (PIN). Again, similar to the results above, we find that the positive impact of financial distress on trade credit is greater for firms with high information opacity. In particular, in Column (2) of Table 2.10, the results show that the coefficient on Distress_Merton × High PIN is significantly positive at the 10% level (t-statistic=2.48). Also, the results from Column (4) show that the coefficient on Distress_Altman × High PIN is significantly positive at the 10% level (t-statistic=2.12). Further, the coefficient on High PIN in Columns (2) and (4) captures how, and whether, firms with high information opacity, due to their high probability of informed trading, use more trade credit. Although we expect that the impact of High PIN on trade credit to be positive and significant, our results in Columns (2) and (4) show that the coefficient on High PIN is insignificant.[33]

Overall, the results in Table 2.10 are consistent with "H2", suggesting that the positive impact of financial distress on the use of trade credit is more pronounced for firms with a more opaque information environment. These results support the view that financially distressed firms having high information opacity are likely to have limited access to sources of financing, as capital market participants may face difficulties in assessing their default risk. On the other hand, given that suppliers have an informational advantage over conventional capital providers (Smith, 1987), they are expected to offer

[33] We replicate results from Columns (2) and (4) of Table 2.10 without controlling for firm-specific characteristics and find a positive impact of high PIN on the trade credit. This impact is especially noticeable when we exclude firm size and the market to book ratio from the model.

more trade credit to their distressed firms having high information opacity. Thus, firms with a more opaque information environment are more sensitive to the increase in financial distress and resort more to trade credit compared to firms with low information opacity. In the next section, we will provide evidence of whether the level of social trust in the county where the firm is headquartered affects the relationship between financial distress and the use of trade credit.

[Insert Table 2.10 here]

2.4.4.2 Social Trust

Our second cross-sectional test investigates whether the impact of financial distress on the use of trade credit varies with the level of social trust in the county where the firm is headquartered. The third hypothesis, "H3," assumes that the positive effect of financial distress on trade credit is greater for firms headquartered in low social trust regions. To test this prediction, we follow the literature (Guiso et al., 2004) and use the level of social capital that can capture the level of mutual trust and altruistic tendencies between people in a society. Prior studies (e.g., Hasan et al., 2017; Jha and Chen, 2015; Jha and Cox, 2015) show that high social capital regions comprise individuals that are more trustworthy, more cooperative, and less self-centred. Thus, firms located in regions with a low social capital are seen as less trustworthy or as those whose potential capital providers are distrustful of them. We use a county-level social capital index developed by Rupasingha et al. (2006). This index is constructed using a principal component analysis based on county-level voter turnout in the presidential election, the number of social and civic associations, the number of non-government organisations and the census response rate. This county-level social capital index is available for the years 1990, 1997, 2005, and 2009. For the years where the social capital index is not available, we suppose that the social capital index in a given county remains the same until a new social capital index becomes available. To identify firms located in low social trust regions, we construct an indicator variable, Low Social Trust, which takes a value of one for firms in the bottom quartile of the social capital index distribution in a given year, and zero otherwise.

We then add the interaction term between financial distress measures and Low Social Trust to Equation 2.1. In this test, the coefficient on Distress_Merton (Distress_Altman) captures the effect of financial distress on the use of trade credit for firms headquartered in high social trust regions, and the coefficient on Distress_Merton (Distress_Altman)

× Low Social Trust captures the impact of financial distress on the use of trade credit for firms headquartered in low social trust regions, relative to those located in high social trust regions. The variable of interest is Distress_Merton (Distress_Altman) × Low Social Trust. According to our third hypothesis, “H3”, we expect the coefficient on Distress_Merton (Distress_Altman) × Low Social Trust to be positive and significant.

The results of this test are presented in Table 2.11. In Column (1), financial distress is measured using the Merton model, while in Column (2), financial distress is measured using the Altman model. The table shows that the coefficient on Distress_Merton × Low Social Trust is positive and significant at the 10% level (t-statistic=1.79). To give a sense of the magnitudes of our results in Column (1), our results suggest that, for firms located in regions characterised by high social trust (i.e., Low Social Trust = 0), the marginal effect of financial distress on trade credit is equal to 0.0150. However, for firms located in regions characterised by low social trust (i.e., Low Social Trust = 1), the marginal effect is 0.0322 (= 0.0150+ 0.0172). In terms of economic magnitude, the coefficient estimate in Column (1) of Table 2.11 suggests that, compared to firms located in regions characterised by high social trust, a one standard deviation increase in the probability of default (Distress_Merton) corresponds to an increase in the use of trade credit by almost 0.24 percentage points (0.0734 × (0.0150+ 0.0172)) for firms located in regions characterised by low social trust. This magnitude is about 2.5% (3.2%) of the mean (median) accounts payable to total assets per standard deviation increase in the probability of default based on the Merton model.

Table 2.11 also presents results using the Altman model (Column 2). The table shows that the coefficient on Distress_Altman × Low Social Trust is positive and significant at the 5% level (t-statistic=2.40). Our results in Column (2) of Table 2.11 suggest that, for firms located in regions characterised by high social trust (i.e., Low Social Trust = 0), the marginal effect of financial distress on trade credit is equal to 0.0128, while for firms located in regions characterised by low social trust (i.e., Low Social Trust = 1), the marginal effect is 0.0254 (= 0.0128+ 0.0126). Further, the economic magnitude of this effect is important, as a one standard deviation increase in the probability of default (Distress_Altman) increases the use of trade credit by about 0.45 percentage points (0.1761 × (0.0128+ 0.0126)) for firms located in low social trust regions. This magnitude is 4.7% (6.1%) of the mean (median) accounts payable to total assets per standard deviation increase in the probability of default based on the Altman Model.

Moreover, the coefficient on Low Social Trust in Columns (1) and (2) captures whether firms with Low Social Trust rely more on trade credit. The results show that the coefficient on Low Social Trust in both Columns (1) and (2) of Table 2.11 is insignificant.

In summary, the results in Table 2.11 are consistent with "H3", indicating that the positive effect of financial distress on the use of trade credit is more pronounced among firms located in regions characterised by a lower level of social trust. This finding supports the idea that firms headquartered in low social trust regions are expected to have more difficulties in accessing sources of financing relative to those located in high social trust regions. This is because capital market participants may perceive firms from low social trust regions to be less trustworthy, as these firms are likely to take actions that may harm capital providers. Thus, the distressed firms located in low social trust regions are expected to use more trade credit, as their suppliers are more willing to help, due to their financing advantages over traditional capital providers.

Our results so far provide strong support that financially distressed firms rely on trade credit as alternative sources of financing, and that this relationship is greater when firms have high information opacity and are located in low social trust regions. An interesting question, however, is whether distressed firms can always rely on trade credit and whether suppliers always help their distressed customers. In the next subsection, we provide further evidence about whether distressed firms can always obtain trade credit from their suppliers.

[Insert Table 2.11 here]

2.4.5 Further Analysis

We have established that distressed firms use more trade to substitute for the lack of alternative sources of financing. Suppliers may be willing to provide liquidity to their distressed customers because they expect the financial distress level of their customers to be not extremely high, and that their distressed customers may not affect their value negatively. However, one may wonder whether suppliers provide liquidity to their distressed customers when those customers negatively affect their value, or whether suppliers can help their distressed customers if they become very risky. In order to uncover these issues, we examine (1) whether being a major customer leads to an to increase the use of trade credit in the case of financial distress, and (2) whether the degree of financial distress affects the use of trade credit.

2.4.5.1 Does Being a Major Customer Affect the Use of Trade Credit?

We now turn to examine whether being a major customer affects the relationship between financial distress and the use of trade credit. Our fourth hypothesis, "H4", implies that the positive impact of financial distress on the use of trade credit is weaker when the firm is a major customer. To test this conjecture, we first partition the sample into low- and high-distress, using the Merton and the Altman models. For the Merton model, we construct two indicator variables: Low_Distress_Merton and High_Distress_Merton. Low_Distress_Merton is an indicator variable that takes a value of one if the firm's probability of default based on Merton's model is 0, and zero otherwise. High_Distress_Merton is an indicator variable that takes a value of one if the firm's probability of default based on Merton's model is greater than 5%, and zero otherwise.[34] For the Altman model, we construct two indicator variables: Low_Distress_Altman and High_Distress_Altman. Low_Distress_Altman is an indicator variable that takes a value of one if the firm's Altman Z score of bankruptcy is greater than 2.99, and zero otherwise. High_Distress_Altman is an indicator variable that takes a value of one if the firm's Altman Z score of bankruptcy is below 1.81, and zero otherwise.[35]

We next use data from the Compustat Segment File "WRDS Supply Chain with IDs" to identify firms that reported as a major customer by its suppliers. Although suppliers are required to report each customer who comprises 10% or above of their sales each year, suppliers regularly voluntarily report their customers who account for less than 10% of their sales. To make sure that the disclosure is not voluntary and to avoid selection bias, we do not consider these firms as major customers. We construct an indicator variable: Major Customer that takes a value of one if a supplier discloses at least one corporate customer that accounts for at least 10% of its total sales, and zero otherwise.[36] We then add the interaction term between Low_Distress_Merton

[34] Since almost 75% of the observations in our sample have zero probability of default based on the Merton (1974) model, in this test, we do not use the top and bottom quartile of the Distress_Merton distribution to identify firms with low and high financial distress. Instead, we consider all firm-year observations in which their probability of default is 0 to be in the low distress group, those with a probability of default above 0 and below 5% to be in the moderate distress group, and those with a probability of default above 5% to be in the high distress group.

[35] We classify these two groups based on Altman's (1968) classifications. We consider firms in which their Altman Z score is between 1.83 and 2.97 to be in the moderate distress group.

[36] For these firms, almost 9% of the observations in our sample are classified as major customers. This figure is close to prior studies that use major customer in their samples (e.g., Cen et al., 2017).

(Low_Distress_Altman) and Major Customer and High_Distress_Merton (High_Distress_Altman) and Major Customer into Equation 2.1.

Table 2.12 presents the results. In Columns (1) through (3), financial distress is measured using the Merton model, while in Columns (4) through (6), financial distress is measured using the Altman model. In Column (1), we only add the interaction term between Low_Distress_Merton and Major customer into Equation 2.1. The results show that the coefficient on Low_Distress_Merton is negative and significant at the 1% level (t-statistic=-4.76), while the coefficient on Low_Distress_Merton × Major Customer is positive but insignificant. In Column (2), we only add the interaction term between High_Distress_Merton and Major customer into Equation 2.1. The results show that the coefficient on High_Distress_Merton is positive and significant at the 1% level (t-statistic=5.63). However, the coefficient on High_Distress_Merton × Major Customer is negative and significant at the 10% level (t-statistic=-2.27), suggesting that the positive impact of financial distress on the use of trade credit is weaker when the firm is a major customer. In other words, financially distressed firms use less trade credit when they are major customers relative to non-major customers. Once again, including both Low_Distress_Merton × Major Customer and High_Distress_Merton × Major Customer in Column (3) yields a negative and significant coefficient on High_Distress_Merton × Major Customer and a positive and insignificant coefficient on Low_Distress_Merton × Major Customer.

Moreover, Column (4) of Table 2.12 includes only the interaction term between Low_Distress_Altman and Major Customer. The results show that the coefficient on Low_Distress_Altman is negative and significant at the 1% level (t-statistic=-12.17). However, the coefficient on Low_Distress_Altman × Major Customer is positive and significant at the 1% level (t-statistic=3.45), suggesting that non-distressed firms use more trade credit when they are major customers relative to non-major customer firms. On the other hand, when condensing only the interaction term between High_Distress_Altman and Major Customer in Column (5) of Table 2.12, the results show that the coefficient on High_Distress_Altman is positive and significant at the 1% level (t-statistic=7.36) and the coefficient on High_Distress_Altman × Major Customer is negative and significant at the 1% level (t-statistic=-3.37). Again, these results also suggest that the positive impact of financial distress on the use of trade credit is less pronounced when the firm is a major customer. Similarly, when we include both Low_Distress_Altman × Major Customer and High_Distress_Altman × Major

Customer in Column (6), we yield a positive and significant coefficient on Low_Distress_Altman × Major Customer and a negative and significant coefficient on High_Distress_Altman × Major Customer.

Moreover, the coefficient on Major Customer in all Columns (1)-(6) captures whether being a major customer leads to an increase in the use of trade credit. The results in Columns (1), (4) and (6) show that the impact of being a major customer on the use of trade credit is insignificant. However, the results in Columns (2), (3) and (5) show that the coefficient on Major Customer is positive and significant. The impact of this variable is greater when we include High_Distress_Merton (High_Distress_Altman) × Major Customer in the model. This finding also supports the view that the major customers receive more trade credit when they are not financially distressed.

Overall, the results in Table 2.12 suggest that financially distressed firms rely less on trade credit when they are major customers relative to non-major customers. At the same time, however, the results suggest that non-distressed firms rely more on trade credit only when they are major customers relative to non-major customers. These findings support the view that suppliers are likely to lose confidence in their distressed major customers, as they are likely to affect their value negatively. Thus, suppliers may stop offering trade credit to their distressed major customers. To uncover whether distressed firms receive less trade credit from their suppliers because they are risky, in the next subsection, we provide more evidence of how a high level of financial distress affects the use of trade credit.

[Insert Table 2.12 here]

2.4.5.2 Does the Degree of Financial Distress Matter?: Examining the Extent to Which There Is a Non-Linear Relationship

In our final set of tests in this chapter, we examine whether the degree of financial distress affects the use of trade credit. Our final hypothesis, “H5”, implies that there is inverted U-shaped relationship between financial distress and the use of trade credit. To test this prediction, we extend the baseline regression model Equation 2.1 by regressing the use of trade credit on financial distress and squared financial distress. In other words, we add the quadratic term of financial distress measures (i.e., $Distress\_Merton^2$ and $Distress\_Altman^2$) to Equation 2.1.

Table 2.13 presents the results for tests of the non-linear relationship between financial distress and the use of trade credit. In Column (1), we use the Merton model, while in Column (2), we use the Altman model. In both measures, the results are consistent with our expectations. Specifically, in Column (1), the coefficient on Distress_Merton is positive and significant at the 1% level (t-statistic=5.80), while the coefficient on Distress_Merton^2 is negative and significant at the 1% level (t-statistic=-4.17). Similarly, in Column (2), the coefficient on Distress_Altman is positive and significant at the 1% level (t-statistic=9.48), and the coefficient on Distress_Altman^2 is negative and significant at the 1% level (t-statistic= -6.70). Taken together, the results in Columns (1) and (2) suggest that the use of trade credit increases when the firm faces financial distress. However, the use of trade credit decreases quadratically with the level of financial distress, and, thus, there is an inverted U-shaped relationship between financial distress and the use of trade credit.

Overall, the results in Table 2.13 suggest that financially distressed firms cannot always rely on trade credit. This is especially true when these firms have a very high financial distress level. Distressed firms can rely on trade credit as long as the level of financial distress is not extremely high. However, when firms face very high default risk, their suppliers may cut the supply of trade credit, as those firms are likely to be risky to the supplier's value. These results are also in line with Garcia-Appendini and Montoriol-Garriga (2020), who find that the use of trade credit decreases when firms approach bankruptcy. The results provide evidence that suppliers' behaviour in helping their distressed customers involves a trade-off between the benefits and costs of helping those customers. Under the assumption that suppliers offer trade credit to identify prospective default risk, suppliers are likely to offer trade credit to their financially distressed customers who face financial distress, but not very high level of financial distress, especially when suppliers make non-salvageable investments in their customers. In this case, by offering trade credit, suppliers may be better placed to take actions to protect those investments. However, suppliers are likely to reduce the supply of trade credit when they signal that their customers face very high levels of financial distress, because suppliers would face moral hazard, in terms of debt repayment, from highly distressed customers. Thus, distressed firms cannot always rely on trade credit financing.

[Insert Table 2.13 here]

2.5 Conclusion

This study is not the first attempt to examine the relationship between financial distress and the use of trade credit. However, our study attempts to enhance our knowledge about this relationship by using diverse measures of financial distress. In particular, we utilise both market-based and accounting-based models of financial distress to revisit the question of whether financially distressed firms rely on trade credit as a source of financing. Prior research shows that market-based models of financial distress outperform accounting-based models, because the former provide more information about default risk that is not available in accounting-based measures. Market-based measures are based on stock price "that can be estimated at any point in time for any publicly-traded firm regardless of the time period and industry" (Hillegeist et al., 2004, p.29). Thus, we argue that the relation between financial distress and the use of trade credit could be more nuanced if we employ different measures of financial distress to examine this relationship.

Based on several theoretical models of trade credit (e.g., Meltzer, 1960; Smith, 1987; Brennan et al., 1988; Biais and Gollier, 1997; Cuñat, 2007), we hypothesise that financially distressed firms rely more on trade credit financing, because suppliers are more likely to help these firms facing difficulties in accessing traditional sources of financing. Using a sample of 99,019 firm-year observations for the period 1976-2017, we find, across all of our financial distress measures, strong evidence of a positive and statistically significant link between financial distress and the use of trade credit. This finding is robust to alternative measures of trade credit, alternative measures of financial distress, alternative model specifications, as well as across different sub-periods.

Furthermore, we address potential concerns about endogeneity bias by conducting five endogeneity tests. This is an issue which has not been satisfactorily addressed in the prior literature. First, we perform propensity score matching (PSM) to account for observable differences between distressed and non-distressed firms. Second, we adopt a high-dimensional fixed effects model to control for unobservable time-varying industry-specific and state-specific heterogeneity. Third, we also estimate a two-stage least squares (2SLS) instrumental variable regression to address the omitted variable bias exploiting firms' differential exposure to aggregate uncertainty shocks in currency, policy, and treasuries to generate exogenous changes in firm-level financial distress. Fourth, we conduct a difference-in-differences (DiD) analysis using the 2007-2008 financial crisis as an exogenous shock to financial distress. Finally, we undertake a triple differences (DiDiD) setup to study the causal effects of financial distress on the use of trade credit, using hurricane strikes as a natural experiment. Overall, these tests confirm our baseline results and further alleviate the concerns related to endogeneity.

Our findings are consistent with the view that when firms face financial distress, their ability to access sources of financing is expected to be limited, as the fear of default prevents capital market participants from providing additional financing. Suppliers, on the other hand, are likely to be more willing to offer trade credit to their financially distressed customers because they have financing advantages over capital providers in investigating the creditworthiness of their distressed customers, monitoring and forcing repayment of the credit in the case of a default (e.g., Smith, 1987; Biais and Gollier, 1997). Also, suppliers are likely to help their financially distressed customers to increase their profit margin through high priced trade credit (Brennan et al., 1988) or because they have an implicit equity stake in their distressed customer's business (Wilner, 2000; Cuñat, 2007). In support of our main hypothesis, we find that the positive impact of financial distress on the use of trade credit is greater for firms with more opaque information environments and firms that are located in low-trust counties. These findings support the view that suppliers' financing advantages over traditional financiers are likely to drive the relationship between financial distress and the use of trade credit.

However, we argue that financially distressed firms may not always rely on trade credit. More specifically, we find that financially distressed firms receive less trade credit when they become very risky and affect suppliers' value negatively. When suppliers are highly dependent on their major customers, to keep supplying and offering trade credit to these firms when they are in financial distress may put suppliers at risk of default (Hertzel et al., 2008; Kolay et al., 2016). Consistent with this argument, we find that the positive impact of financial distress on the use of trade credit is weaker when the firms are major customers of their suppliers. Furthermore, suppliers may lose confidence in their distressed customers when they become very risky. This is especially true when the firm's default is imminent and under the assumption that the recovery rates for suppliers are low in case of default. In support of this argument, we find that firms increase their trade credit when they are financially distressed and decrease their use of trade credit when they face a very high level of financial distress, suggesting an inverted-U pattern between financial distress and the use of trade credit.

These findings are consistent with Garcia-Appendini and Montoriol-Garriga (2020), who document an average decrease in the use of trade credit as firms approach bankruptcy events.

Overall, this study suggests that financially distressed firms cannot always rely on trade credit. Financially distressed firms use trade credit to substitute for the lack of alternative sources of financing. However, suppliers may offer trade credit to these firms only when they expect their customers' financial distress level to not be very high. Having established that firms that face financial distress use more trade credit, because they have limited access to other sources of financing, as their capital providers may be worried about the firm's default risk, in the next chapter, we will consider a source of information that is likely to be crucial to capital market participants in assessing the firm's default risk and which could affect the use of trade credit. In particular, we examine the relationship between segment information disclosure and the use of trade credit.

Tables-Chapter 2

Table 2.1. Descriptive Statistics

Table 2.1 presents the descriptive statistics. Panel A of this table reports sample distribution by year over the period 1976-2017. Panel B reports summary statistics of all variables used in our analysis for the entire sample of 99,019 firm-years. Panel C reports the mean of trade credit and financial distress across industries based on the Fama–French 12 Industry classification. Panel D reports the correlation matrix between all variables used in the analysis. All variable definitions and sources of data are described in the Appendix.

Panel A: Sample Distribution of Firms by Year

Year	N	Percent	AP/TA
1976	2217	2.24	0.1083
1977	2146	2.17	0.1103
1978	2187	2.21	0.1145
1979	2265	2.29	0.1133
1980	2226	2.25	0.1093
1981	2184	2.21	0.1018
1982	2292	2.31	0.1049
1983	2236	2.26	0.1067
1984	2370	2.39	0.1007
1985	2349	2.37	0.1002
1986	2326	2.35	0.1048
1987	2419	2.44	0.1089
1988	2442	2.47	0.1061
1989	2418	2.44	0.1069
1990	2400	2.42	0.1035
1991	2431	2.46	0.1015
1992	2533	2.56	0.0998
1993	2678	2.70	0.1028
1994	2899	2.93	0.1032
1995	3043	3.07	0.1007
1996	3130	3.16	0.0992
1997	3218	3.25	0.0950
1998	3087	3.12	0.0950
1999	2903	2.93	0.0958
2000	2830	2.89	0.0860
2001	2819	2.85	0.0825
2002	2669	2.70	0.0806
2003	2554	2.58	0.0823
2004	2438	2.46	0.0842
2005	2371	2.40	0.0833
2006	2268	2.30	0.0836
2007	2233	2.26	0.0797
2008	2234	2.26	0.0765
2009	2100	2.12	0.0809
2010	1991	2.01	0.0810
2011	1922	1.94	0.0798
2012	1863	1.88	0.0788
2013	1804	1.82	0.0781
2014	1754	1.77	0.0762
2015	1722	1.74	0.0779
2016	1662	1.68	0.0809
2017	1386	1.40	0.0799

Panel B: Descriptive Statistics of the Full Sample

Variable	N	Mean	Std.dev.	p1	p25	Median	p75	p99
AP/TA	99019	0.0947	0.0779	0.0049	0.0419	0.0736	0.1216	0.4230
Distress_Merton	99019	0.0211	0.0734	0.0000	0.0000	0.0000	0.0004	0.4520
Distress_Altman	99019	0.0880	0.1761	0.0000	0.0042	0.0253	0.0826	0.9940
Firm Size	99019	5.3610	1.9483	1.4327	3.9393	5.2338	6.6616	10.3600
Firm Age	99019	18.4200	13.4644	3.0000	8.0000	15.0000	26.0000	60.0000
Tangibility	99019	0.2870	0.2133	0.0135	0.1185	0.2337	0.4011	0.8790
Cost of Goods Sold	99019	0.9170	0.7132	0.0441	0.4205	0.7610	1.2006	3.9280
Negative Growth	99019	-0.0380	0.0939	-0.5144	-0.0108	0.0000	0.0000	0.0000
Positive Growth	99019	0.1830	0.2929	0.0000	0.0000	0.0901	0.2217	1.8570
MTB	99019	1.7640	1.5456	0.5709	0.9925	1.3247	1.9623	7.6950
Capital Expenditure	99019	0.0650	0.0636	0.0022	0.0233	0.0452	0.0827	0.3480
R&D	99019	0.0372	0.0685	0.0000	0.0000	0.0000	0.0448	0.3730
ROA	99019	0.0067	0.1602	-0.8410	-0.0067	0.0434	0.0828	0.2490
Cash Holding	99019	0.1500	0.1743	0.0003	0.0254	0.0798	0.2124	0.7690
Leverage	99019	0.2230	0.1952	0.0000	0.0491	0.1965	0.3403	0.8650
Market Share	99019	0.0481	0.1090	0.0000	0.0008	0.0059	0.0358	0.6730

Panel C: Descriptive Statistics by Industry

	N	Percent	AP/TA	Distress_Merton	Distress_Altman
Consumer non-durables	8507	8.59	0.0926	0.0206	0.0536
Consumer durables	3892	3.93	0.1092	0.0259	0.0633
Manufacturing	17407	17.58	0.0954	0.0207	0.0662
Energy	4747	4.79	0.0872	0.0285	0.1529
Chemicals	3511	3.55	0.1014	0.0153	0.0644
Business Equipment	22784	23.01	0.0802	0.0137	0.1104
Telcom	2613	2.64	0.0523	0.0341	0.2099
Wholesale and Retail	14175	14.32	0.1518	0.0270	0.0474
Health	9041	9.13	0.0649	0.0154	0.1136
Others	12342	12.46	0.0829	0.0268	0.0926

Panel D: Correlation Matrix

		1	2	3	4	5	6	7	8
1	AP/TA								
2	Distress_Merton	0.09							
3	Distress_Altman	0.03	0.30						
4	Firm Size	-0.12	-0.11	-0.13					
5	Firm Age	-0.02	-0.09	-0.10	0.47				
6	Tangibility	-0.10	0.07	0.03	0.19	0.06			
7	Cost of Goods Sold	0.55	0.06	-0.15	-0.09	0.02	-0.03		
8	Negative Growth	-0.01	-0.14	-0.28	0.13	0.02	0.03	0.07	
9	Positive Growth	-0.01	-0.04	-0.01	-0.08	-0.23	-0.05	-0.08	0.25
10	MTB	-0.07	-0.13	-0.03	-0.05	-0.11	-0.16	-0.14	0.06
11	Capital Expenditure	-0.04	-0.03	-0.02	0.04	-0.10	0.63	-0.04	0.08
12	R&D	-0.10	-0.06	0.26	-0.20	-0.16	-0.29	-0.25	-0.12
13	ROA	-0.11	-0.24	-0.61	0.26	0.17	0.06	0.04	0.36
14	Cash Holding	-0.21	-0.14	0.04	-0.18	-0.18	-0.38	-0.26	-0.10
15	Leverage	0.02	0.39	0.30	0.16	0.01	0.30	0.00	-0.02
16	Market Share	0.04	-0.05	-0.09	0.42	0.29	0.04	0.09	0.07

		9	10	11	12	13	14	15	16
9	Positive Growth		0.23	0.13	0.07	0.00	0.11	-0.01	-0.08
10	MTB			0.02	0.29	-0.02	0.32	-0.15	-0.04
11	Capital Expenditure				-0.11	0.06	-0.17	0.10	-0.03
12	R&D					-0.38	0.46	-0.23	-0.16
13	ROA						-0.12	-0.14	0.12
14	Cash Holding							-0.41	-0.15
15	Leverage								0.07
16	Market Share								

Table 2.2.Univariate Analysis

This table reports the univariate analysis of the use of trade credit and the firm-specific characteristics of the distressed and non-distressed firms in the full sample, using a t-test for difference in means. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively. We classify firms as distressed firms using the probability of default of Merton's (1974) Distance-to-Default model and Altman (1968) Z score. Distressed1 is an indicator variable equal to one for firm-year observations in the top quartile of the Distress_Merton distribution, and zero otherwise. Distressed2 is an indicator variable equal to one if the firm's Altman Z score is below 1.81 and zero otherwise. Columns (1) through (3) present results for the Merton model. Columns (4) through (6) present results for the Altman Model. All variable definitions and sources of data are described in the Appendix.

Variable	Distressed (Distressed1=1)	Non-Distressed (Distressed1=0)	Difference (t-stat)	Distressed (Distressed2=1)	Non-Distressed (Distressed2=0)	Difference (t-stat)
AP/TA	0.1138	0.0882	0.0256***	0.0980	0.0960	0.0020**
Firm Size	4.7127	5.5762	-0.8634***	5.1339	5.4029	-0.2690***
Firm Age	15.3832	19.4271	-4.0439***	15.5288	18.9584	-3.4296***
Tangibility	0.3158	0.2767	0.0390***	0.3462	0.2753	0.0709***
Cost of Goods Sold	1.0288	0.8792	0.1495***	0.5941	0.9770	-0.3829***
Negative Growth	-0.0635	-0.0294	-0.0340***	-0.0888	-0.0284	-0.0604***
Positive Growth	0.1645	0.1886	-0.0240***	0.1827	0.1826	0.0001
MTB	1.2019	1.9517	-0.7497***	1.4863	1.8166	-0.3302***
Capital Expenditure	0.0605	0.0665	-0.0059***	0.0649	0.0650	-0.0011
R&D	0.0297	0.0396	-0.0099***	0.0568	0.0335	0.0233***
ROA	-0.0739	0.0335	-0.1075***	-0.1638	0.0387	-0.2026***
Cash Holding	0.0937	0.1691	-0.0754***	0.1412	0.1520	-0.0107***
Leverage	0.3844	0.1698	0.2145***	0.3923	0.1917	0.2005***
Market Share	0.0291	0.0543	-0.0252***	0.0278	0.0518	-0.0240***
N	24,736	74,283		15,634	83,385	

Table 2.3. Baseline Evidence: Financial Distress and the Use of Trade Credit

This table reports the regressions results of the effect of financial distress on the use of trade credit. The dependent variable is the use of trade credit, defined as the ratio of accounts payable to total assets. Columns (1) through (2) present the regression results for the probability of default based on Merton's (1974) Distance-to-Default model. Columns (3) through 4 present the regression results for the probability of default based on the Altman (1968) model. Regressions in Columns (1) and (3) include industry (SIC 3-dight) and year fixed effects. Regressions in Columns (2) and (4) include firm and year fixed effects. T-statistics are given in parentheses beneath the coefficients. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the firm level and robust to heteroscedasticity. All independent variables are lagged by one year. All variable definitions and sources of data are described in the Appendix.

	Dependent variable = AP/TA			
	[1]	[2]	[3]	[4]
Distress_Merton	0.0416***	0.0187***		
	(8.15)	(4.93)		
Distress_Altman			0.0362***	0.0204***
			(11.20)	(7.23)
Firm Size	-0.0027***	-0.0075***	-0.0025***	-0.0068***
	(-6.56)	(-10.38)	(-6.15)	(-9.34)
Firm Age	-0.0013*	0.0009	-0.0015**	0.0000
	(-1.77)	(0.62)	(-1.96)	(0.01)
Tangibility	-0.0593***	-0.0429***	-0.0600***	-0.0428***
	(-15.18)	(-9.46)	(-15.37)	(-9.44)
Cost of Goods Sold	0.0524***	0.0391***	0.0531***	0.0393***
	(33.82)	(21.96)	(34.38)	(22.13)
Negative Growth	-0.0028	0.0051**	0.0013	0.0071***
	(-0.88)	(2.14)	(0.41)	(2.96)
Positive Growth	0.0051***	0.0037***	0.0046***	0.0037***
	(5.11)	(4.83)	(4.65)	(4.86)
MTB	0.0019***	0.0001	0.0019***	0.0002
	(6.35)	(0.27)	(6.58)	(0.88)
Capital Expenditure	0.0496***	0.0094**	0.0471***	0.0086*
	(7.80)	(2.02)	(7.41)	(1.86)
R&D	-0.0111	0.0218**	-0.0310***	0.0118
	(-1.18)	(2.46)	(-3.22)	(1.32)
ROA	-0.0676***	-0.0341***	-0.0548***	-0.0298***
	(-22.83)	(-14.29)	(-18.88)	(-12.46)
Cash Holding	-0.0679***	-0.0429***	-0.0670***	-0.0420***
	(-20.89)	(-15.04)	(-20.67)	(-14.72)
Leverage	-0.0041	0.0076***	-0.0078***	0.0041*
	(-1.54)	(3.22)	(-2.78)	(1.67)
Market Share	0.0431***	0.0228***	0.0410***	0.0218***
	(6.78)	(2.80)	(6.47)	(2.69)
Intercept	0.0770***	0.1133***	0.0749***	0.1099***
	(13.37)	(21.85)	(12.80)	(21.22)
N	99019	99019	99019	99019
R^2	0.4796	0.1399	0.4822	0.1416
Industry effects	Yes	No	Yes	No
Firm effects	No	Yes	No	Yes
Year effects	Yes	Yes	Yes	Yes

Table 2.4. Robustness Tests

Panel A: Alternative Measures of Trade Credit

This table presents the results of the additional analyses, the purpose of which is to examine whether our results are robust to alternative ways of defining the use of trade credit. Columns (1) through (2) present results for the dependent variable accounts payable, scaled by the cost of goods sold. Columns (3) through (4) present results for the dependent variable accounts payable, scaled by sales. Columns (1) and (3) present the regression results for the probability of default based on Merton's (1974) Distance-to-Default model. Columns (2) and (4) present the regression results for the probability of default based on the Altman (1968) model. All regressions include firm and year fixed effects. T-statistics are given in parentheses beneath the coefficients. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the firm level and robust to heteroscedasticity. All independent variables are lagged by one year. All variable definitions and sources of data are described in the Appendix.

	Dependent variable = AP/COGS		Dependent variable = AP/SALE	
	[1]	[2]	[3]	[4]
Distress_Merton	0.0224***		0.0243***	
	(3.12)		(6.05)	
Distress_Altman		0.0415***		0.0320***
		(5.72)		(10.06)
Firm Size	-0.0087***	-0.0071***	-0.0087***	-0.0007
	(-5.51)	(-4.53)	(-5.32)	(-1.05)
Firm Age	-0.0100***	-0.0119***	-0.0097***	-0.0113***
	(-3.61)	(-4.34)	(-3.34)	(-9.53)
Tangibility	-0.0184**	-0.0187**	-0.0202**	-0.0119***
	(-2.04)	(-2.08)	(-2.19)	(-2.88)
Cost of Goods Sold	-0.0502***	-0.0499***	-0.0527***	-0.0028**
	(-15.16)	(-15.13)	(-15.07)	(-2.32)
Negative Growth	-0.2019***	-0.1972***	-0.1980***	-0.1313***
	(-27.05)	(-26.31)	(-25.93)	(-39.05)
Positive Growth	-0.0353***	-0.0352***	-0.0347***	-0.0198***
	(-16.49)	(-16.48)	(-15.91)	(-21.85)
MTB	0.0012*	0.0015**	0.0011*	0.0011***
	(1.84)	(2.31)	(1.70)	(4.19)
Capital Expenditure	0.0083	0.0085	0.0142	0.0118**
	(0.64)	(0.66)	(1.05)	(2.24)
R&D	0.1466***	0.1271***	0.1474***	0.0055
	(6.43)	(5.40)	(6.33)	(0.57)
ROA	0.0187***	0.0280***	0.0239***	-0.0439***
	(3.12)	(4.77)	(3.86)	(-16.79)
Cash Holding	-0.0405***	-0.0387***	-0.0389***	-0.0106***
	(-5.67)	(-5.46)	(-5.34)	(-3.68)
Leverage	0.0212***	0.0117**	0.0183***	0.0076***
	(4.12)	(2.28)	(3.50)	(3.25)
Market Share	0.0275**	0.0253**	0.0290**	0.0107*
	(2.39)	(2.21)	(2.47)	(1.79)
Intercept	0.2163***	0.2095***	0.2174***	0.0945***
	(20.08)	(19.56)	(19.24)	(21.64)
N	99019	99019	99019	99019
R^2	0.1122	0.1142	0.1132	0.2237
Firm effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes

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Panel B: Alternative Measures of Financial Distress

This table presents the results of the additional analyses, the purpose of which is to examine whether our results are robust to alternative measures of financial distress. Column (1) presents the regression results for the probability of default based on the Ohlson (1980) model. Column (2) presents the regression results for the probability of default based on the Campbell et al. (2008) model. All regressions include firm and year fixed effects. T-statistics are given in parentheses beneath the coefficients. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the firm level and robust to heteroscedasticity. All independent variables are lagged by one year. All variable definitions and sources of data are described in the Appendix

	Dependent variable = AP/TA	
	[1]	[2]
Distress_Ohlson	0.0355***	
	(20.18)	
Distress_Campbell		0.0118***
		(5.93)
Firm Size	-0.0057***	-0.0074***
	(-7.97)	(-10.11)
Firm Age	0.0013	0.0012
	(0.94)	(0.80)
Tangibility	-0.0438***	-0.0422***
	(-9.86)	(-9.22)
Cost of Goods Sold	0.0369***	0.0390***
	(21.18)	(21.67)
Negative Growth	0.0107***	0.0062***
	(4.40)	(2.58)
Positive Growth	0.0038***	0.0033***
	(5.08)	(4.23)
MTB	-0.0001	0.0000
	(-0.49)	(0.09)
Capital Expenditure	0.0086*	0.0085*
	(1.90)	(1.79)
R&D	0.0005	0.0213**
	(0.06)	(2.44)
ROA	-0.0082***	-0.0314***
	(-3.23)	(-12.92)
Cash Holding	-0.0377***	-0.0408***
	(-13.54)	(-14.28)
Leverage	-0.0196***	0.0076***
	(-6.90)	(3.22)
Market Share	0.0220***	0.0251***
	(2.75)	(3.09)
Intercept	0.0997***	0.1099***
	(19.71)	(20.87)
N	99019	95001
R^2	0.1535	0.1419
Firm effects	Yes	Yes
Year effects	Yes	Yes

Panel C: Financial Distress Measures Based on Principal Component Analysis (PCA)

This table presents the results of the additional analyses, the purpose of which is to examine whether our results are robust when we aggregate the four measures of financial distress using a principal component analysis. Panel C1 presents the results from a principal component analysis (PCA) based on Distress_Merton, Distress_Altman, Distress_Ohlson, and Distress_Campbell. The eigenvalue, the proportion of variance explained by the 1st, 2nd, 3rd, and 4th component, and the eigenvectors on each of the four financial distress measures of the 1st component is presented. Panel C2 reports the correlation coefficients among the financial distress measures and the first principal component of these measures. Panel C3 resorts regression results on the effect of the financial distress, using the first principal component of the four financial distress measures (PC1), on the use of trade credit. The regression include firm and year fixed effects. Control variables (same as those reported in Table 2.3) are included in the regression but are not reported in the interest of brevity. T-statistics are given in parentheses beneath the coefficients. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the firm level and robust to heteroscedasticity. All independent variables are lagged by one year. All variable definitions and sources of data are described in the Appendix.

Panel C1: Estimation Results of Principal Component Analysis of the Financial Distress Measures

Eigenvalue of the correlation matrix				Factor loading of the first component	
	Eigenvalue	Difference	Cumulative percentage of the total variance	Variables	Eigenvector
PC1	2.3754	1.5963	59.39%	Distress_Merton	0.4809
PC2	0.7791	0.2803	78.87%	Distress_Altman	0.4899
PC3	0.4988	0.1522	91.34%	Distress_Ohlson	0.5047
PC4	0.3465	-	100%	Distress_Campbell	0.5234

Panel C2: Correlation between the First Principal Component and Financial Distress Measures

		1	2	3	4	5
1	PC1					
2	Distress_Merton	0.74				
3	Distress_Altman	0.75	0.30			
4	Distress_Ohlson	0.77	0.41	0.55		
5	Distress_Campbell	0.80	0.57	0.46	0.42	

Panel C3: Regression Results Using the First Principal Component of the Financial Distress Variables

	Dependent variable: AP/TA
	[1]
PC1	0.0036***
	(12.56)
Intercept	0.1097***
	(20.99)
N	95001
R^2	0.1465
Firm effects	Yes
Year effects	Yes
Controls	Yes

Panel D: Alternative Estimators: Fama-MacBeth and Two-Way Cluster

This table presents the results of the additional analyses, the purpose of which is to examine whether our results are robust to alternative model specifications. The dependent variable is the use of trade credit, defined as the ratio of accounts payable to total assets. Column (1) presents the regression results for the probability of default based on Merton's (1974) Distance-to-Default model. Column (2) presents the regression results for the probability of default based on the Altman (1968) model. In Estimation (1), we extend the baseline model in Table 2.3 by using Fama-MacBeth estimations. In Estimation (2), we use two-way clusters by firm and year. In Estimation (3), we use two-way clusters by industry and year. In Estimation (1), we control for industry fixed effects. In Estimations (2) and (3), we control for firm and year fixed effects. In all Estimations (1)-(3), we include the same control variables used in Table 2.3 but are not reported in the interest of brevity. T-statistics are given in parentheses beneath the coefficients. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the firm level and robust to heteroscedasticity. All independent variables are lagged by one year. All variable definitions and sources of data are described in the Appendix.

	Dependent variable = AP/TA	
	[1]	[2]
Estimation (1): Fama-MacBeth regression		
Distress_Merton	0.0373***	
	(7.67)	
Distress_Altman		0.0545***
		(11.54)
Intercept	0.0798***	0.0841***
	(4.96)	(5.14)
N	99019	99019
R^2	0.5379	0.5426
Controls	Yes	Yes
Industry effects	Yes	Yes
Year effects	No	No
Estimation (2): Two-way clustering by firm and year		
Distress_Merton	0.0187***	
	(5.87)	
Distress_Altman		0.0204***
		(9.88)
Intercept	0.1145***	0.1116***
	(42.06)	(40.92)
N	99019	99019
R^2	0.1399	0.1416
Controls	Yes	Yes
Firm effects	Yes	Yes
Year effects	Yes	Yes
Estimation (3): Two-way clustering by industry and year		
Distress_Merton	0.0187***	
	(5.61)	
Distress_Altman		0.0204***
		(8.92)
Intercept	0.1145***	0.1116***
	(37.41)	(35.82)
N	99019	99019
R^2	0.1399	0.1416
Controls	Yes	Yes
Firm effects	Yes	Yes
Year effects	Yes	Yes

Panel E: Sub-Period Analysis

This table presents the results of the additional analyses, the purpose of which is to examine whether our results are robust to different sample periods. The table reports the effects of financial distress on the use of trade credit in four subperiods (1976–1986, 1987–1997, 1998–2008, and 2009–2017). The dependent variable is the use of trade credit, defined as the ratio of accounts payable to total assets. Column (1) presents the regression results for the probability of default based on Merton's (1974) Distance-to-Default model. Column (2) presents the regression results for the probability of default based on the Altman (1968) model. All regressions include firm and year fixed effects. Control variables (same as those reported in Table 2.3) are included in all regressions but are not reported in the interest of brevity. T-statistics are given in parentheses beneath the coefficients. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the firm level and robust to heteroscedasticity. All independent variables are lagged by one year. All variable definitions and sources of data are described in the Appendix.

	Dependent variable = AP/TA	
	[1]	[2]
Period (1): 1976-1986		
Distress_Merton	-0.0044	
	(-0.45)	
Distress_Altman		0.0190*
		(1.93)
Intercept	0.1601***	0.1588***
	(14.15)	(13.99)
N	24798	24798
R^2	0.0702	0.0711
Controls	Yes	Yes
Firm effects	Yes	Yes
Year effects	Yes	Yes
Period (2): 1987-1997		
Distress_Merton	0.0197***	
	(2.95)	
Distress_Altman		0.0199***
		(3.04)
Intercept	0.1414***	0.1384***
	(15.87)	(15.45)
N	29611	29611
R^2	0.0699	0.0708
Controls	Yes	Yes
Firm effects	Yes	Yes
Year effects	Yes	Yes
Period (3): 1998-2008		
Distress_Merton	0.0138***	
	(2.83)	
Distress_Altman		0.0142***
		(4.32)
Intercept	0.1247***	0.1216***
	(12.45)	(12.18)
N	28406	28406
R^2	0.0856	0.0871
Controls	Yes	Yes
Firm effects	Yes	Yes
Year effects	Yes	Yes
Period (4): 2009-2017		
Distress_Merton	0.0162*	
	(1.68)	
Distress_Altman		0.0169***
		(3.00)
Intercept	0.1147***	0.1068***
	(7.39)	(7.05)
N	16204	16204
R^2	0.0746	0.0772
Controls	Yes	Yes
Firm effects	Yes	Yes
Year effects	Yes	Yes

Table 2.5. Mitigating Endogeneity: Propensity Score Matching Analysis

This table reports the results of propensity score matching estimation. We match each distressed firm to a non-distressed firm using a one-to-one propensity score matching to the nearest neighbourhood without replacement. We classify firms as distressed firms using the probability of default of Merton's (1974) Distance-to-Default model and Altman (1968) Z score. Distressed1 is an indicator variable equal to one for firm-year observations in the top quartile of the Distress_Merton distribution, and zero otherwise. Distressed2 is an indicator variable equal to one if the firm's Altman Z score is below 1.81 and zero otherwise. Panel A reports parameter estimates from the logit model used to estimate propensity scores. Columns (1) through (2) present results for the Merton model. Columns (3) through (4) present results for the Altman model. The matching is based on firm size, firm age, industry, and year. Panel B presents the distribution of propensity scores from the regression in Columns (2) and (4) of Panel A. Panel C presents the univariate comparisons of firm characteristics (i.e., size and age) and trade credit between distressed and non-distressed firms. Columns (1) through (3) present results for the Merton model. Columns (4) through (6) present results for the Altman Model. Panel D reports the regression results for the matched samples. Column (1) presents results for the Merton model. Column (2) presents results for the Altman model. All regressions in Panel D include firm and year fixed effects and the same control variables used in Table 2.3. T-statistics are given in parentheses beneath the coefficients. ∗∗∗ ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the firm level and robust to heteroscedasticity. All independent variables are lagged by one year. All variable definitions and sources of data are described in the Appendix.

Panel A: Pre-Match Propensity Score Regression and Post-Match Diagnostic Regression

	Dependent variable= Distressed1		Dependent variable= Distressed2	
	[1] Pre-match	[2] Post-match	[3] Pre-match	[4] Post-match
Firm Size	-0.3373***	0.0007	-0.1731***	0.0005
	(-28.23)	(0.05)	(-11.26)	(0.03)
Firm Age	-0.0138***	0.0013	-0.0177***	-0.0022
	(-7.32)	(0.70)	(-7.04)	(-0.91)
Intercept	0.4849	-0.0322	-1.2979***	0.2344
	(1.05)	(-0.06)	(-3.32)	(0.55)
N	99019	46222	99019	27800
Pseudo R^2	0.0951	0.0021	0.1575	0.0038
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes

Panel B: Estimated Propensity Score Distributions

Propensity score	Mean	Std.dev.	Min	P25	P50	P75	Max
Distressed1 (obs. = 23,111)	0.03084	0.1247	0.009	0.2164	0.3010	0.3901	0.9030
Non-Distressed1 (obs. = 23,111)	0.03084	0.1247	0.009	0.2164	0.3010	0.3901	0.9030
Difference	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Distressed2 (obs. = 13,900)	0.2474	0.1480	0.0011	0.1381	0.21805	0.3238	0.8017
Non-Distressed2 (obs. = 13,900)	0.2474	0.1480	0.0011	0.1381	0.21805	0.3238	0.8018
Difference	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0001

Panel C: Differences in Firm Size, Firm Age and Trade Credit

	[1]	[2]	[3]	[4]	[5]	[6]
Variable	Distressed (Distressed1=1)	Non-Distressed (Distressed1=0)	Difference (t-stat)	Distressed (Distressed2=1)	Non-Distressed (Distressed2=0)	Difference (t-stat)
Firm Size	4.7754	4.7532	0.0221	5.0931	5.0947	-0.0015
			(1.35)			(-0.06)
Firm Age	15.6470	15.5183	0.1287	15.7350	15.9412	-0.2062
			(1.20)			(-1.40)
AP/TA	0.1137	0.0935	0.0202***	0.0948	0.0806	0.0142***
			(26.30)			(14.61)
N	23,111	23,111		13,900	13,900	

Panel D: Multivariate Analysis Using Propensity-Score-Matched Samples

	Dependent variable = AP/TA	
	[1]	[2]
Distressed1	0.0039***	
	(4.86)	
Distressed2		0.0056***
		(4.85)
N	46222	27800
R^2	0.1251	0.1191
Control	Yes	Yes
Firm effects	Yes	Yes
Year effects	Yes	Yes

Table 2.6. Mitigating Endogeneity: High-Dimensional Fixed Effects

This table presents the regression results of the effect of financial distress on the use of trade credit, including high-dimensional fixed effects at the firm, year-industry and state-year level. State-year fixed effects are based on the location of the firm's headquarters. Industry-year fixed effects are based on the SIC 3-digit codes. The dependent variable is the ratio of accounts payable to total assets. Columns (1) through (2) present the regression results for the probability of default based on Merton's (1974) Distance-to-Default model. Columns (3) through (4) present the regression results for the probability of default based on the Altman (1968) model. Regressions in Columns (1) and (3) include firm and industry-year fixed. Regressions in Columns (2) and (4) include firm, industry-year and state-year fixed effects. T-statistics are given in parentheses beneath the coefficients. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the firm level and robust to heteroscedasticity. All independent variables are lagged by one year. All variable definitions and sources of data are described in the Appendix.

	Dependent variable = AP/TA			
	[1]	[2]	[3]	[4]
Distress_Merton	0.0205***	0.0213***		
	(5.11)	(5.21)		
Distress_Altman			0.0213***	0.0213***
			(7.54)	(7.41)
Firm Size	-0.0081***	-0.0080***	-0.0071***	-0.0070***
	(-10.53)	(-10.06)	(-9.24)	(-8.77)
Firm Age	0.0019	0.0020	0.0010	0.0011
	(1.29)	(1.33)	(0.67)	(0.73)
Tangibility	-0.0382***	-0.0381***	-0.0382***	-0.0381***
	(-8.21)	(-7.88)	(-8.22)	(-7.89)
Cost of Goods Sold	0.0372***	0.0378***	0.0375***	0.0381***
	(20.71)	(20.30)	(20.90)	(20.50)
Negative Growth	0.0039	0.0035	0.0059**	0.0055**
	(1.51)	(1.30)	(2.30)	(2.06)
Positive Growth	0.0027***	0.0025***	0.0027***	0.0025***
	(3.38)	(3.01)	(3.38)	(3.02)
MTB	0.0000	0.0000	0.0002	0.0002
	(0.04)	(0.08)	(0.57)	(0.59)
Capital Expenditure	0.0092*	0.0097*	0.0083*	0.0087*
	(1.91)	(1.94)	(1.73)	(1.74)
R&D	0.0124	0.0109	0.0027	0.0013
	(1.36)	(1.17)	(0.29)	(0.14)
ROA	-0.0330***	-0.0331***	-0.0283***	-0.0284***
	(-13.45)	(-13.05)	(-11.55)	(-11.20)
Cash Holding	-0.0436***	-0.0439***	-0.0426***	-0.0429***
	(-15.19)	(-14.95)	(-14.85)	(-14.61)
Leverage	0.0104***	0.0103***	0.0067***	0.0067***
	(4.58)	(4.49)	(2.81)	(2.75)
Market Share	0.0350***	0.0366***	0.0314***	0.0328***
	(3.44)	(3.49)	(3.10)	(3.14)
Intercept	0.1148***	0.1133***	0.1108***	0.1091***
	(18.29)	(17.30)	(17.65)	(16.63)
N	99019	93237	99019	93237
R^2	0.1223	0.1258	0.1242	0.1278
Firm effects	Yes	Yes	Yes	Yes
Industry ×Year effects	Yes	Yes	Yes	Yes
State ×Year effects	No	Yes	No	Yes

Table 2.7. Mitigating Endogeneity: Instrumental Variable Approach

This table presents the instrumental variable regression results of the effect of financial distress on the use of trade credit. We undertake a two-stage least squares (2SLS) regression with nine aggregate sources of uncertainty shocks as the instrumental variable. These include the exposure to annual changes in expected volatility of seven widely traded currencies, 10-year treasuries, and economic policy uncertainty from Baker et al.(2016). The first-stage regressions (i.e., Columns (1) and (3)) generate the fitted (instrumented) value of financial distress measures for use in the second stage regressions (i.e., Columns (2) and (4)). Columns (1) through (2) present the regression results for the probability of default based on Merton's (1974) Distance-to-Default model. Columns (3) through (4) present the regression results for the probability of default based on the Altman (1968) model. All regressions include firm and year fixed effects. All regressions include firm and year fixed effects. Control variables (same as those reported in Table 2.3 and the first moment of the nine instruments) are included in all regressions but are not reported in the interest of brevity. T-statistics are given in parentheses beneath the coefficients. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the firm level and robust to heteroscedasticity. All independent variables are lagged by one year. All variable definitions and sources of data are described in the Appendix.

	[1]	[2]	[3]	[4]
	2SLS- Merton		2SLS- Altman	
	First Stage	Second Stage	First Stage	Second Stage
	Distress_Merton	AP/TA	Distress_Altman	AP/TA
Instrumented_Distress_Merton		0.1325**		
		(2.28)		
Instrumented_Distress_Altman				0.2315*
				(1.77)
Vol Exposure Aud	0.1108*		0.0452	
	(1.93)		(0.47)	
Vol Exposure Cad	-0.0980		0.2835***	
	(-1.27)		(2.94)	
Vol Exposure Chf	0.0981**		0.0029	
	(2.04)		(0.05)	
Vol Exposure Euro	0.1029**		-0.0020	
	(2.38)		(-0.03)	
Vol Exposure Gbp	0.4434***		-0.0373	
	(3.86)		(-0.35)	
Vol Exposure Jpy	0.2558**		-0.4367***	
	(2.30)		(-2.72)	
Vol Exposure Sek	0.0284		0.2144***	
	(0.45)		(2.67)	
Vol Exposure Policy	38.6593**		19.6556	
	(2.04)		(0.80)	
Vol Expos Treasury	0.0001**		0.0000	
	(2.18)		(0.61)	
N	40344	40344	40344	40344
R^2	0.1575	0.0965	0.3458	-0.0244
Controls	Yes	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Wald F-test 1st stage Cragg-Donald	12.148		1.822	
Hansen J (p-value)		0.2541		0.2406

Table 2.8. Mitigating Endogeneity: Difference-in-Differences (DiD) Analysis: Evidence from the 2007-2008 Financial Crisis

This table reports results using a difference-in-differences (DiD) analysis of the effects of high leverage and low-interest coverage at the beginning of the 2007-2008 financial crisis on the use of trade credit. The dependent variable is the use of trade credit, defined as the ratio of accounts payable to total assets. In Column (1), Treat_(High_Leverage) is an indicator variable equal to one for firms in the top quartile of leverage distribution during one year before the crisis (i.e., the year 2007). In Column (2), Treat_(Low_Interest_Cov) is an indicator variable equal to one for firms in the bottom quartile of interest coverage ratio distribution during one year before the crisis . In Column (3), Treat_(Interest_Cov_Below_One) is an indicator variable equal to one if the firm's interest coverage ratio is less than one during one year before the crisis . In all Columns (1)-(3), After_Crisis is an indicator variable equal to one for the year after the crisis (i.e., 2008). All regressions include firm and year fixed effects. T-statistics are given in parentheses beneath the coefficients. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the firm level and robust to heteroscedasticity. All variable definitions and sources of data are described in the Appendix.

	Dependent variable = AP/TA		
	[1]	[2]	[3]
Treat_(High_Leverage) × After Crisis	0.0030**		
	(2.00)		
Treat_(Low_Interest_Cov) × After Crisis		0.0059***	
		(2.89)	
Treat_(Interest_Cov_Below_One) × After Crisis			0.0099***
			(3.37)
After Crisis	-0.0102*	-0.0102**	-0.0101**
	(-1.92)	(-1.97)	(-1.97)
Firm Size	-0.0041	-0.0010	-0.0006
	(-0.78)	(-0.18)	(-0.11)
Firm Age	0.0341*	0.0308	0.0297
	(1.85)	(1.63)	(1.59)
Tangibility	-0.1099***	-0.1043***	-0.1022***
	(-3.29)	(-3.13)	(-3.09)
Cost of Goods Sold	0.0141	0.0138	0.0141
	(1.47)	(1.41)	(1.45)
Negative Growth	0.0321***	0.0310***	0.0297***
	(4.13)	(3.93)	(3.73)
Positive Growth	0.0067	0.0072	0.0071
	(0.87)	(0.94)	(0.92)
MTB	0.0016*	0.0018**	0.0020**
	(1.75)	(1.97)	(2.22)
Capital Expenditure	0.0230	0.0222	0.0211
	(0.76)	(0.73)	(0.69)
R&D	-0.0247	-0.0399	-0.0478
	(-0.62)	(-0.98)	(-1.17)
ROA	-0.0471***	-0.0539***	-0.0546***
	(-4.54)	(-4.60)	(-4.68)
Cash Holding	-0.0820***	-0.0835***	-0.0830***
	(-5.37)	(-5.45)	(-5.44)
Leverage		-0.0269**	-0.0275**
		(-2.13)	(-2.20)
Market Share	-0.0359**	-0.0335**	-0.0336**
	(-2.56)	(-2.36)	(-2.41)
Intercept	0.0453	0.0403	0.0404
	(0.70)	(0.63)	(0.63)
N	4034	4034	4034
R^2	0.1273	0.1338	0.1363
Firm effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes

Table 2.9. Mitigating Endogeneity: Triple Difference-in-Differences (DiDiD) Analysis: Evidence from Hurricane Strikes

This table presents results using a triple difference-in-differences (DiDiD) of the effect of changes in the firm's financial distress on the use of trade credit, using hurricane strikes as a quasi-natural experiment. The dependent variable is the ratio of accounts payable to total assets. Treat_(Hurricane) is an indicator variable equal to one for firm-year observations associated with firms located in a hurricane-struck county over the 6 year-period surrounding a hurricane strike, and zero otherwise. After_Hurricane is an indicator variable equal to one for the 3 years after a hurricane strike, and zero otherwise. Distress_Merton is defined as an indicator variable equal to one for firms in the top quartile of the Distress-Merton distribution (during one year before the hurricane strike). Distress_Altman is defined as an indicator variable equal to one if the firm's Altman Z score is below 1.81 (during one year before the hurricane strike), and zero otherwise. Columns (1) and (3) include the full sample of both treated and control firms. Columns (2) and (4) exclude from the control group sample those associated with firms located within 50 miles of each struck county. Columns (3) and (6) include a matched sample, in which hurricane struck firms are matched with non- hurricane struck firms based on one-to-one propensity score matching. Propensity scores are obtained from a logit regression of a dummy variable equal to one for observations associated with the hurricane-struck firms (during one year before hurricane strike) on a set of matching variables, including firm size, firm age, tangibility, market-to-book ratio, leverage, R&D, ROA, sales growth, cash holding, market share and SIC three-dight industry dummies. All regressions include firm and year fixed effects. T-statistics are given in parentheses beneath the coefficients. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the firm level and robust to heteroscedasticity. All variable definitions and sources of data are described in the Appendix.

	Dependent variable = AP/TA					
	[1]	[2]	[3]	[4]	[5]	[6]
Treat_(Hurricane) × After_Hurricane	-0.0032	-0.0013	-0.0032	-0.0013	-0.0023	0.0007
	(-1.02)	(-0.49)	(-1.01)	(-0.49)	(-0.58)	(0.17)
Treat_(Hurricane) × Distress_Merton × After_Hurricane	0.0093**		0.0093**		0.0143**	
	(2.02)		(2.01)		(2.38)	
Treat_(Hurricane) × Distress_Altman × After_Hurricane		0.0091*		0.0092*		0.0139*
		(1.66)		(1.68)		(1.92)
Treat_(Hurricane) × Distress_Merton	-0.0149**		-0.0151**		-0.0138**	
	(-2.35)		(-2.33)		(-2.03)	
Treat_(Hurricane) × Distress_Altman		-0.0136**		-0.0137**		-0.0192***
		(-2.26)		(-2.25)		(-2.61)
Distress_Merton × After_Hurricane	-0.0002		-0.0002		-0.0020	
	(-0.34)		(-0.33)		(-0.77)	
Distress_Altman × After_Hurricane		0.0012**		0.0011*		-0.0011
		(1.96)		(1.78)		(-0.40)
Treated	0.0068	0.0030	0.0069	0.0030	0.0053	0.0036
	(1.47)	(0.74)	(1.46)	(0.73)	(0.88)	(0.78)
After_Hurricane	0.0124***	0.0120***	0.0127***	0.0124***	0.0078	0.0077
	(3.44)	(3.34)	(3.51)	(3.42)	(0.55)	(0.52)
Firm Size	-0.0061***	-0.0061***	-0.0061***	-0.0061***	-0.0024	-0.0024
	(-8.16)	(-8.16)	(-8.14)	(-8.13)	(-0.93)	(-0.95)
Firm Age	-0.0010	-0.0010	-0.0010	-0.0010	0.0009	0.0008
	(-0.72)	(-0.72)	(-0.73)	(-0.72)	(0.16)	(0.15)
Tangibility	-0.0627***	-0.0627***	-0.0629***	-0.0629***	-0.0627***	-0.0619***
	(-13.82)	(-13.81)	(-13.79)	(-13.79)	(-3.85)	(-3.81)
Cost of Goods Sold	0.0493***	0.0493***	0.0492***	0.0492***	0.0620***	0.0621***
	(26.56)	(26.55)	(26.35)	(26.33)	(8.08)	(8.12)
Negative Growth	0.0156***	0.0156***	0.0158***	0.0159***	0.0053	0.0059
	(6.69)	(6.70)	(6.76)	(6.78)	(0.68)	(0.78)
Positive Growth	0.0075***	0.0075***	0.0074***	0.0074***	0.0100***	0.0095***
	(9.55)	(9.52)	(9.36)	(9.33)	(3.27)	(3.14)
MTB	0.0015***	0.0015***	0.0014***	0.0014***	0.0005	0.0005
	(5.97)	(5.95)	(5.76)	(5.74)	(0.51)	(0.48)
Capital Expenditure	0.0520***	0.0519***	0.0531***	0.0530***	0.0709***	0.0682***
	(11.42)	(11.41)	(11.58)	(11.57)	(3.68)	(3.54)
R&D	0.0173*	0.0174*	0.0176*	0.0177*	-0.0323	-0.0293
	(1.89)	(1.90)	(1.90)	(1.91)	(-0.95)	(-0.88)
ROA	-0.0370***	-0.0372***	-0.0369***	-0.0370***	-0.0351***	-0.0356***
	(-15.19)	(-15.24)	(-15.01)	(-15.05)	(-4.06)	(-4.15)
Cash Holding	-0.0718***	-0.0718***	-0.0717***	-0.0716***	-0.0609***	-0.0606***
	(-24.81)	(-24.81)	(-24.58)	(-24.57)	(-6.38)	(-6.34)
Leverage	-0.0030	-0.0031	-0.0029	-0.0030	0.0120	0.0110
	(-1.25)	(-1.27)	(-1.20)	(-1.22)	(1.11)	(1.02)
Market Share	0.0185**	0.0184**	0.0178**	0.0177**	0.0800*	0.0750*
	(2.17)	(2.16)	(2.10)	(2.09)	(1.93)	(1.81)
Intercept	0.0957***	0.0957***	0.0957***	0.0956***	0.0586***	0.0587***
	(17.82)	(17.82)	(17.68)	(17.68)	(3.15)	(3.17)
N	83925	83925	82671	82671	4124	4124
R^2	0.2356	0.2356	0.2357	0.2357	0.3266	0.3272
Firm effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.10. Cross-Sectional Analysis: The Role of Information Opacity

This table reports the heterogeneous effects of financial distress on the use of trade credit conditional on the firm's information opacity. The dependent variable is the use of trade credit, defined as the ratio of accounts payable to total assets. Columns (1) and (3) present the results when information opacity is proxied by the number of analysts following the firm. Low Analyst is an indicator variable equal to one for firms in the bottom quartile of the firm's number of analysts following distribution in a given year, and zero otherwise. Columns (2) and (4) present the results when information opacity is proxied by the probability of informed trading (PIN). High PIN is an indicator variable equal to one for firms in the top quartile of PIN distribution in a given and zero otherwise. Columns (1) through (2) present the regression results for the probability of default based on Merton's (1974) Distance-to-Default model. Columns (3) through (4) present the regression results for the probability of default based on the Altman (1968) model. The total impact of financial distress on the use of trade credit with Low Analyst (High PIN)= 0 is captured by the coefficient on Distress_Merton (Distress_Altman). The total impact of financial distress on the use of trade credit with Low Analyst (High PIN) = 1 is the sum of the coefficients on Distress_Merton (Distress_Altman) and Distress_Merton (Distress_Altman) × Low Analyst (High PIN). All regressions include firm and year fixed effects. T-statistics are given in parentheses beneath the coefficients. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the firm level and robust to heteroscedasticity. All independent variables are lagged by one year. All variable definitions and sources of data are described in the Appendix.

	Dependent variable = AP/TA			
	[1]	[2]	[3]	[4]
Distress_Merton	0.0025	0.0094*		
	(0.59)	(1.82)		
Distress_Merton × Low Analyst	0.0300***			
	(4.60)			
Distress_Merton × High PIN		0.0176**		
		(2.48)		
Distress_Altman			0.0116***	0.0123***
			(4.08)	(3.66)
Distress_Altman × Low Analyst			0.0157***	
			(4.36)	
Distress_Altman × High PIN				0.0092**
				(2.12)
Low Analyst	0.0041***		0.0032***	
	(4.94)		(3.67)	
High PIN		-0.0003		-0.0009
		(-0.40)		(-1.19)
Firm Size	-0.0066***	-0.0089***	-0.0058***	-0.0081***
	(-9.03)	(-9.54)	(-7.93)	(-8.69)
Firm Age	0.0004	0.0015	-0.0005	0.0003
	(0.29)	(0.75)	(-0.37)	(0.15)
Tangibility	-0.0426***	-0.0240***	-0.0425***	-0.0240***
	(-9.40)	(-4.85)	(-9.39)	(-4.86)
Cost of Goods Sold	0.0391***	0.0300***	0.0394***	0.0302***
	(22.03)	(14.98)	(22.27)	(15.07)
Negative Growth	0.0048**	0.0072**	0.0066***	0.0085***
	(1.98)	(2.47)	(2.75)	(2.89)
Positive Growth	0.0035***	0.0026***	0.0035***	0.0026***
	(4.56)	(2.70)	(4.60)	(2.72)
MTB	0.0001	-0.0004	0.0002	-0.0002
	(0.41)	(-1.35)	(0.79)	(-0.83)
Capital Expenditure	0.0103**	0.0022	0.0095**	0.0007
	(2.23)	(0.38)	(2.05)	(0.13)
R&D	0.0241***	0.0098	0.0155*	0.0028
	(2.73)	(0.90)	(1.74)	(0.26)
ROA	-0.0339***	-0.0323***	-0.0298***	-0.0294***
	(-14.24)	(-10.20)	(-12.48)	(-9.52)
Cash Holding	-0.0424***	-0.0343***	-0.0414***	-0.0334***
	(-14.87)	(-9.88)	(-14.51)	(-9.62)
Leverage	0.0071***	0.0049*	0.0044*	0.0022
	(3.00)	(1.66)	(1.79)	(0.71)
Market Share	0.0216***	0.0219**	0.0204**	0.0214**
	(2.67)	(2.49)	(2.52)	(2.44)
Intercept	0.1068***	0.1247***	0.1037***	0.1225***
	(20.34)	(19.21)	(19.79)	(18.91)
N	99019	45370	99019	45370
R^2	0.1416	0.1045	0.1434	0.1059
Firm effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes

Table 2.11. Cross-sectional Analysis: The Role of Social Trust

This table reports the heterogeneous effects of financial distress on the use of trade credit conditional on the degree of social trust. The dependent variable is the use of trade credit, defined as the ratio of accounts payable to total assets. Social trust is measured using a county-level measure of social capital in the region where the firm has its headquarters (obtained from Rupasingha et al.(2006)). Low Social Trust is an indicator variable equal to one for all firms in a year when the social trust index is in the bottom quartile of the sample period and zero otherwise. The total impact of financial distress on the use of trade credit with Low Social Trust = 0 is captured by the coefficient on Distress_Merton (Distress_Altman). The total impact of financial distress on the use of trade credit with Low Social Trust = 1 is the sum of the coefficients on Distress_Merton (Distress_Altman) and Distress_Merton (Distress_Altman) × Low Social Trust. Column (1) presents the regression results for the probability of default based on Merton's (1974) Distance-to-Default model. Column (2) presents the regression results for the probability of default based on the Altman (1968) model. All regressions include firm and year fixed effects. T-statistics are given in parentheses beneath the coefficients. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the firm level and robust to heteroscedasticity. All independent variables are lagged by one year. All variable definitions and sources of data are described in the Appendix.

	Dependent variable = AP/TA	
	[1]	[2]
Distress_Merton	0.0150***	
	(3.23)	
Distress_Merton × Low Social Trust	0.0172*	
	(1.79)	
Distress_Altman		0.0128***
		(3.92)
Distress_Altman × Low Social Trust		0.0126**
		(2.40)
Low Social Trust	-0.0007	-0.0016
	(-0.47)	(-1.01)
Firm Size	-0.0089***	-0.0082***
	(-11.44)	(-10.41)
Firm Age	0.0001	-0.0010
	(0.06)	(-0.58)
Tangibility	-0.0290***	-0.0289***
	(-6.10)	(-6.09)
Cost of Goods Sold	0.0349***	0.0352***
	(19.12)	(19.26)
Negative Growth	0.0054**	0.0065**
	(2.03)	(2.43)
Positive Growth	0.0022**	0.0022**
	(2.48)	(2.53)
MTB	-0.0002	-0.0001
	(-0.84)	(-0.38)
Capital Expenditure	0.0052	0.0040
	(0.91)	(0.71)
R&D	0.0226**	0.0142
	(2.41)	(1.49)
ROA	-0.0281***	-0.0244***
	(-10.03)	(-8.75)
Cash Holding	-0.0367***	-0.0358***
	(-11.90)	(-11.65)
Leverage	0.0076***	0.0051*
	(3.05)	(1.92)
Market Share	0.0323***	0.0314***
	(4.03)	(3.94)
Intercept	0.1183***	0.1157***
	(19.72)	(19.30)
N	66820	66820
R^2	0.1293	0.1308
Firm effects	Yes	Yes
Year effects	Yes	Yes

Table 2.12. Further Analysis: The Impact of Being a Major Customer

This table reports the regression results of the impact of being a major customer on the relation between financial distress and the use of trade credit. The dependent variable is the use of trade credit, defined as the ratio of accounts payable to total assets. Major Customer is an indicator variable that takes a value of one if a supplier discloses at least one corporate customer that accounts for at least 10% of its total sales, and zero otherwise. Columns (1) through (3) present the regression results for the Merton model. Columns (4) through (6) present the regression results for the Altman model. Low_Distress_Merton is an indicator variable that takes a value of one if the firm's probability of default based on Merton's model is zero, and zero otherwise. High_Distress_Merton is an indicator variable that takes a value of one if the firm's probability of default based on Merton's model is greater than 5%, and zero otherwise. Low_Distress_Altman is an indicator variable that takes a value of one if the firm's Altman Z score of bankruptcy is above 2.99, and zero otherwise. High_Distress_Altman is an indicator variable that takes a value of one if the firm's Altman Z score of bankruptcy is below 1.81, and zero otherwise. All regressions include firm and year fixed effects. T-statistics are given in parentheses beneath the coefficients. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the firm level and robust to heteroscedasticity. All independent variables are lagged by one year. All variable definitions and sources of data are described in the Appendix.

	Dependent variable = AP/TA					
	[1]	[2]	[3]	[4]	[5]	[6]
Low_Distress_Merton	-0.0024***		-0.0027***			
	(-4.76)		(-5.37)			
High_Distress_Merton		0.0049***	0.0053***			
		(5.63)	(6.02)			
Low_Distress_Merton × Major Customer	0.0018		0.0014			
	(1.33)		(1.00)			
High_Distress_Merton × Major Customer		-0.0066**	-0.0062**			
		(-2.27)	(-2.19)			
Low_Distress_Altman				-0.0081***		-0.0073***
				(-12.17)		(-11.24)
High_Distress_Altman					0.0066***	0.0045***
					(7.36)	(5.15)
Low_Distress_Altman × Major Customer				0.0062***		0.0047**
				(3.45)		(2.54)
High_Distress_Altman × Major Customer					-0.0075***	-0.0042*
					(-3.37)	(-1.85)
Major Customer	0.0016	0.0028**	0.0021*	-0.0016	0.0034***	-0.0002
	(1.34)	(2.44)	(1.73)	(-1.13)	(2.78)	(-0.10)
Firm Size	-0.0077***	-0.0077***	-0.0076***	-0.0076***	-0.0075***	-0.0074***
	(-10.68)	(-10.66)	(-10.49)	(-10.56)	(-10.39)	(-10.30)
Firm Age	0.0011	0.0009	0.0010	0.0007	0.0006	0.0004
	(0.76)	(0.65)	(0.68)	(0.46)	(0.39)	(0.27)
Tangibility	-0.0424***	-0.0430***	-0.0431***	-0.0430***	-0.0432***	-0.0435***
	(-9.35)	(-9.48)	(-9.51)	(-9.51)	(-9.53)	(-9.61)
Cost of Goods Sold	0.0391***	0.0390***	0.0389***	0.0402***	0.0394***	0.0403***
	(22.04)	(21.97)	(21.96)	(22.50)	(22.19)	(22.53)
Negative Growth	0.0044*	0.0052**	0.0053**	0.0055**	0.0061**	0.0066***
	(1.83)	(2.14)	(2.19)	(2.31)	(2.54)	(2.76)
Positive Growth	0.0035***	0.0037***	0.0036***	0.0036***	0.0036***	0.0036***
	(4.65)	(4.85)	(4.71)	(4.81)	(4.72)	(4.77)
MTB	0.0001	0.0001	0.0002	0.0003	0.0001	0.0003
	(0.57)	(0.32)	(0.82)	(1.23)	(0.53)	(1.38)
Capital Expenditure	0.0076*	0.0093**	0.0099**	0.0104**	0.0094**	0.0115**
	(1.65)	(2.02)	(2.13)	(2.25)	(2.02)	(2.48)
R&D	0.0202**	0.0212**	0.0209**	0.0191**	0.0177**	0.0173**
	(2.28)	(2.39)	(2.36)	(2.17)	(2.00)	(1.97)
ROA	-0.0341***	-0.0342***	-0.0334***	-0.0295***	-0.0323***	-0.0283***
	(-14.26)	(-14.31)	(-14.02)	(-12.29)	(-13.59)	(-11.81)
Cash Holding	-0.0423***	-0.0428***	-0.0422***	-0.0406***	-0.0423***	-0.0404***
	(-14.83)	(-14.99)	(-14.80)	(-14.22)	(-14.83)	(-14.16)
Leverage	0.0085***	0.0078***	0.0054**	0.0030	0.0066***	0.0011
	(3.51)	(3.35)	(2.21)	(1.27)	(2.77)	(0.46)
Market Share	0.0224***	0.0221***	0.0220***	0.0224***	0.0224***	0.0224***
	(2.77)	(2.74)	(2.73)	(2.79)	(2.77)	(2.78)
Intercept	0.1143***	0.1138***	0.1141***	0.1183***	0.1127***	0.1169***
	(22.24)	(22.13)	(22.22)	(23.18)	(21.93)	(22.93)
N	99019	99019	99019	99019	99019	99019
R^2	0.1397	0.1401	0.1405	0.1409	0.1428	0.1434
Firm effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.13. Further Analysis: Nonlinear Relationship between Financial Distress and the Use of Trade Credit

This table reports regressions of the use of trade credit on financial distress and the square of financial distress. The dependent variable is the ratio of accounts payable to total assets. Column (1) presents the regression results for the probability of default based on Merton's (1974) Distance-to-Default model. Column (2) presents the regression results for the probability of default based on the Altman (1968) model. All regressions include firm and year fixed effects. T-statistics are given in parentheses beneath the coefficients. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the firm level and robust to heteroscedasticity. All independent variables are lagged by one year. All variable definitions and sources of data are described in the Appendix.

	Dependent variable = AP/TA	
	[1]	[2]
Distress_Merton	0.0550***	
	(5.80)	
Distress_Merton^2	-0.0882***	
	(-4.17)	
Distress_Altman		0.0660***
		(9.48)
Distress_Altman^2		-0.0513***
		(-6.70)
Firm Size	-0.0075***	-0.0069***
	(-10.31)	(-9.49)
Firm Age	0.0009	0.0000
	(0.60)	(0.02)
Tangibility	-0.0432***	-0.0436***
	(-9.52)	(-9.60)
Cost of Goods Sold	0.0390***	0.0401***
	(21.95)	(22.43)
Negative Growth	0.0054**	0.0082***
	(2.23)	(3.42)
Positive Growth	0.0037***	0.0036***
	(4.86)	(4.79)
MTB	0.0001	0.0004*
	(0.42)	(1.70)
Capital Expenditure	0.0103**	0.0121***
	(2.21)	(2.59)
R&D	0.0218**	0.0149*
	(2.46)	(1.67)
ROA	-0.0339***	-0.0271***
	(-14.18)	(-11.27)
Cash Holding	-0.0428***	-0.0404***
	(-14.99)	(-14.13)
Leverage	0.0065***	-0.0006
	(2.78)	(-0.23)
Market Share	0.0227***	0.0228***
	(2.79)	(2.81)
Intercept	0.1129***	0.1078***
	(21.78)	(20.78)
N	99019	99019
R^2	0.1403	0.1434
Firm effects	Yes	Yes
Year effects	Yes	Yes

Appendix-Chapter 2

Table 2.A1. Variable Definitions

This table presents variable definitions and their source. All variables in italics are Compustat, CRSP, and IBES data items.

Variable	Definition	Data sources
Trade credit variables		
AP/TA	The ratio of accounts payable (*ap*) to total assets (*at)*	Compustat
AP/COGS	The ratio of accounts payable (*ap*) to cost of goods sold (*cogs*).	Compustat
AP/SALE	The ratio of accounts payable (*ap*) sales (*sale).*	Compustat
Financial distress variables		
Merton	Merton's (1974) Distance-to-Default model calculated following Bharath and Shumway (2008) equation 12, defined as $\mathrm{Merton} = \mathrm{N}\left(-\frac{\ln[\mathrm{E+F})/\mathrm{F}] + (\mu - 0.50\,\sigma^2 \mathrm{v})\,\mathrm{T}}{\sigma\mathrm{v}\sqrt{\mathrm{T}}}\right)$, where N is the cumulative standard normal distribution function, E is the market value of equality in millions of dollars (CRSP monthly items *prc* × (*shrout/*1000)), F is the face value of debt, calculated as debt in current liabilities (Compustat item *dlc)* plus one half of the long term debt (Compustat item *dltt* × 0.50), μ is the expected return, computed as the firm's stock return over the previous year (CRSP monthly item *ret*). σv is the assets volatility, approximated as $\sigma\mathrm{v} = \frac{\mathrm{E}}{\mathrm{E+F}} \times \sigma\mathrm{E} + \frac{\mathrm{F}}{\mathrm{E+F}} \times (0.05 + 0.25\sigma\mathrm{E})$,where σE is the volatility of a firm's stock return (CRSP daily item *ret*), calculated as an annualized 12 months rolling sample standard deviation multiplied by the square root of the average number of trading days in the year (set at 252 trading days). T is the maturity of debt, assumed to be one year. The probability of Default based on the Merton model is the cumulative standard normal distribution of the negative distance to default.	Compustat; CRSP
Altman	Altman (1968) Z-score, calculated using his equation page 594 as $\mathrm{Z} = 1.20 \times \mathrm{X1} + 1.40 \times \mathrm{X3} + 3.30 \times \mathrm{X3} + 0.60 \times \mathrm{X4} + 0.999 \times \mathrm{X5}$, where X1 is the ratio of working capital (Compustat items *act-lct*) to total assets, X2 is the ratio of retained earnings (Compustat item *re*) to total assets, X3 is the ratio of earnings before interest (Compustat item *oiadp*) to total assets, X4 is the ratio of the market value of equity to total liabilities (Compustat item: *lt*), and X5 is the ratio of total sales (Compustat item: *sale*) to total assets. The probability of default based on the Altman model is exp(Altman Z-score *-1) / 1 + exp(Altman Z-score *-1).	Compustat
Ohlson	Ohlson (1980) O-score, calculated using his Table 4, defined as $\mathrm{O} = -1.32 - 0.407 \times \mathrm{SIZE} + 6.03 \times \mathrm{TLTA} - 1.43 \times \mathrm{WCTA} + 0.0757 \times \mathrm{CLCA} - 2.37 \times \mathrm{NITA} - 1.83 \times \mathrm{FULT} + 0.285 \times \mathrm{INTWO} - 1.72 \times \mathrm{OENEG} - 0.521 \times \mathrm{CHIN}$, where SIZE is the logarithm of the total assets (*at*) adjusted for inflation, as measured by the Gross National Product (GNP) Index, TLTA is the ratio of total liabilities (*lt*) to total assets (*at*), WCTA is the ratio of working capital (*act-lct)* to total assets (*at*), CLCA is the ratio of current liabilities (*lct*) to total assets (*at*), NITA is the ratio of net income (*ni*) to total assets (*at*), FULT is the ratio of funds provided by operations (*pi*+*dp*) to total liabilities (*lt*), INTWO is a dummy variable that is equal to one if the firm has had a negative net income (*ni*) in the last two years, and zero otherwise, OENEG is a dummy variable that is equal to one if the firm's total liabilities (*lt*) exceed total assets (*at*). and zero otherwise, and CHIN is the change in the firm's net income, calculated as $\frac{ni_t - ni_{t-1}}{\lvert ni_t \rvert + \lvert ni_{t-1} \rvert}$. The probability of default based on the Ohlson model is exp(Ohlson O-score) / 1 + exp(Ohlson O-score).	Compustat

Campbell	Campbell et al. (2008) discrete time hazard model, calculated using their Table 4 as $\text{Campbell} = -9.08 - 29.67 \times \text{NIMTAAVG} + 3.36 \times \text{TLMTA} - 7.35 \times \text{EXRETAVG} + 1.48 \times \text{SIGMA} + 0.082 \times \text{RSIZE} - 2.40 \times \text{CASHMTA} + 0.054 \times \text{MB} - 0.937 \times \text{Log Price}$, where NITMAAVG is the geomantic average of the ratio of net income to the market value of equity plus total liabilities, TLMTA is the ratio of total liabilities to the market value of equity plus total liabilities, EXRETAVG is the geomantic average of the log monthly return on the firm minus the log monthly return on the S&P 500 index (CRSP monthly item *sprtrn*), SIGMA is the standard deviation of daily stock returns, RSIZE is the log market value of equity divided by the log market value on the S&P 500 index (index file on S&P500 (from CRSP) item *totval*), CASHMTA is the ratio of cash and short term investments (Compustat item *che*) to the market value of equity plus total liabilities, MB is the ratio of the market value of equity to the adjusted value of the book value of equity (Compustat items *at*-*lt*+*txditc*+*pstk*), where the adjusted value of the book value of equity is calculated as $\text{book value of equity} + (0.1 * \text{market value of equity})$, then we replace negative values by one. The log Price is the log monthly stock price truncated above 15 (CRSP monthly item *prc*). The probability of default based on the Campbell et al. model is exp(Campbell) / 1 + exp(Campbell).	Compustat CRSP
Firm-specific characteristics		
Firm Size	The natural logarithm of total assets (*at*) in millions of U.S. dollars.	Compustat
Firm Age	The natural logarithm of the current year minus the year the Compustat database first begins tracking data for the firm plus one.	Compustat
Tangibility	The ratio of the total property, plant and equipment (*ppent*) to total assets (*at*).	Compustat
Cost of Goods Sold	The ratio of cost of goods sold (*cogs*) to total assets (*at*).	Compustat
Sales Growth	The percentage change in a firm's sales in the current year relative to the previous year (*sale* t - *sale* t-1)/*sale* t-1).	Compustat
Negative Growth	Sales growth times the negative growth dummy, which is equal to one if sales growth is negative and 0 otherwise.	Compustat
Positive Growth	Sales growth times the positive growth dummy, which is equal to one if sales growth is positive and 0 otherwise.	Compustat
Capital Expenditure	The ratio of capital expenditures (*capx*) to total assets (*at*)	Compustat
R&D	The ratio of research and development (*xrd*) to total assets (*at*).	Compustat
ROA	The ratio of operating income before depreciation (*oibdp*) to total assets (*at*).	Compustat
MTB	The ratio market value of assets over book value of assets, which is calculated as follows: [(*prcc_f* ∗ *csho*)-(*at*-*lt* + *txditc*) + *at*]/*at*.	Compustat
Cash Holding	The ratio of cash and short term investments (*che*) to total assets (*at*).	Compustat
Leverage	The ratio of total debt (*dltt*+*dlc*) to total assets (*at*).	Compustat
Market Share	The ratio of a firm's sales to total sales in its industry (SIC three-dight).	Compustat
Other variables		
Interest Coverage Ratio	The ratio of earnings before interest, taxes, depreciation, and amortization (*ebitda*) divided by interest expense (*xint*).	
Analysts Following	The total number of estimates (IBES item *numest*) over the entire year.	IBES

PIN	The Probability of informed trade, computed based on Stephen Brown's calculation as PIN = $\frac{(\text{mu} \times \text{alpha})}{\text{mu}\times\text{alpha} + 2 \times \text{epsi}}$, where mu is the trading intensity of informed traders, alpha is the probability of an information event, and epsi is the trading intensity of uninformed traders.	http://scholar.rhsmith.umd.edu/sbrown/pin-data
Social Trust	Rupasingha et al.'s (2006) county-level social capital index.	https://aese.psu.edu/nercrd/community/social-capital-resources
Major Customer	Is an indicator variable equal to one if a firm discloses at least one corporate customer that accounts for at least 10% of its total sales, and zero otherwise.	Compustat's Customers Segment Database

Table 2.A2. Variance Inflation Factors

This table presents the mean variance inflation factor (VIF) of all independent variables to quantify the severity of multicollinearity.

Variable	Mean VIF	VIF is estimated from
Distress_Merton	1.33	Column 1 of Table 2.3
Distress_Altman	1.79	Column 3 of Table 2.3
Firm Size	2.30	Column 1 of Table 2.3
Firm Age	1.65	Column 1 of Table 2.3
Tangibility	3.70	Column 1 of Table 2.3
Cost of Goods Sold	2.10	Column 1 of Table 2.3
Negative Growth	1.36	Column 1 of Table 2.3
Positive Growth	1.30	Column 1 of Table 2.3
MTB	2.09	Column 1 of Table 2.3
Capital Expenditure	2.08	Column 1 of Table 2.3
R&D	1.63	Column 1 of Table 2.3
ROA	1.37	Column 1 of Table 2.3
Cash Holding	1.94	Column 1 of Table 2.3
Leverage	1.70	Column 1 of Table 2.3
Market Share	2.08	Column 1 of Table 2.3

Table 2.A3. Robustness of Distance to Default Model Calculation

This table presents results for the additional robustness checks of Merton's (1974) Distance-to-Default model calculation. Distress_Merton is calculated by simultaneously solving two nonlinear equations and implementing an iterative process based on the Black–Scholes–Merton pricing model. We use the SAS program as in Hillegeist et al.(2004.P30) to solve the two equations simultaneously for the two unknown variables, the market value of assets and asset volatility. Column (1) includes industry and year fixed effects. Column (2) includes firm and year fixed effects. T-statistics are given in parentheses beneath the coefficients. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the firm level and robust to heteroscedasticity. All independent variables are lagged by one year. All variable definitions and sources of data are described in the Appendix.

	Dependent variable = AP/TA	
	[1]	[2]
Distress_Merton	0.0361***	0.0085***
	(10.76)	(4.00)
Firm Size	-0.0022***	-0.0076***
	(-5.30)	(-10.38)
Firm Age	-0.0013*	0.0010
	(-1.67)	(0.69)
Tangibility	-0.0590***	-0.0412***
	(-15.05)	(-8.96)
Cost of Goods Sold	0.0534***	0.0391***
	(34.31)	(22.88)
Negative Growth	-0.0006	0.0046*
	(-0.20)	(1.86)
Positive Growth	0.0050***	0.0034***
	(5.00)	(4.40)
MTB	0.0021***	0.0001
	(6.88)	(0.43)
Capital Expenditure	0.0488***	0.0083*
	(7.61)	(1.77)
R&D	-0.0110	0.0220**
	(-1.17)	(2.43)
ROA	-0.0656***	-0.0344***
	(-21.67)	(-14.03)
Cash Holding	-0.0642***	-0.0417***
	(-20.03)	(-14.48)
Leverage	-0.0026	0.0105***
	(-0.95)	(4.37)
Market Share	0.0434***	0.0235***
	(6.70)	(2.82)
Intercept	0.0713***	0.1120***
	(12.37)	(21.59)
N	95286	95286
R^2	0.4845	0.1391
Industry effects	Yes	No
Firm effects	No	Yes
Year effects	Yes	Yes

Table 2.A4. Robustness of the Altman Z Score Model

This table presents results for the additional robustness checks of the Altman Z score model in which the original Altman model is modified. The modified Altman Z score is a modified version of the Z score that does not include leverage (Graham et al., 1998). Column (1) includes industry and year fixed effects. Column (2) includes firm and year fixed effects. T-statistics are given in parentheses beneath the coefficients. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the firm level and robust to heteroscedasticity. All independent variables are lagged by one year. All variable definitions and sources of data are described in the Appendix.

	Dependent variable = AP/TA	
	[1]	[2]
Distress_Modified_Altman	0.0207***	0.0221***
	(6.34)	(6.32)
Firm Size	-0.0026***	-0.0068***
	(-6.29)	(-9.02)
Firm Age	-0.0011	0.0002
	(-1.50)	(0.15)
Tangibility	-0.0599***	-0.0436***
	(-15.33)	(-9.62)
Cost of Goods Sold	0.0539***	0.0401***
	(34.49)	(22.08)
Negative Growth	-0.0024	0.0071***
	(-0.76)	(2.97)
Positive Growth	0.0041***	0.0035***
	(4.07)	(4.58)
MTB	0.0015***	-0.0000
	(5.22)	(-0.12)
Capital Expenditure	0.0455***	0.0087*
	(7.16)	(1.88)
R&D	-0.0264***	0.0109
	(-2.71)	(1.21)
ROA	-0.0541***	-0.0246***
	(-15.65)	(-9.13)
Cash Holding	-0.0684***	-0.0419***
	(-20.96)	(-14.51)
Leverage	-0.0016	0.0066***
	(-0.59)	(2.82)
Market Share	0.0410***	0.0221***
	(6.45)	(2.71)
Intercept	0.0718***	0.1056***
	(11.97)	(19.24)
N	99019	99019
R^2	0.4797	0.1399
Industry effects	Yes	No
Firm effects	No	Yes
Year effects	Yes	Yes

Chapter 3 Segment Information Disclosure and Trade Credit: Evidence from a Quasi-Natural Experiment

Abstract

Using the adoption of SFAS 131 as a quasi-natural experiment, this chapter examines the impact of segment information disclosure on a firm's use of trade credit. SFAS 131 requires firms to disclose previously "hidden" segment information, which leads to a revision in capital market participants' beliefs about the firm's diversification activities. As a result, capital market participants' information asymmetry with respect to the co-insurance effect provided by the firm's true underlying diversification may be reduced. We find strong evidence that firms that improved their segment disclosure by revealing new information about their segments upon adoption of SFAS 131 decrease their use of trade credit after the adoption of SFAS 131. This is consistent with predictions in the theoretical literature that firms rely more (less) on trade credit when the information asymmetry between firms and capital providers is higher (lower). In line with the improvement in the firm's information environment, such an impact is concentrated among change (treatment) firms with high default risk, a more opaque information environment, weak governance, and with non-Big 4 auditors before the adoption of SFAS 131. Our results suggest that the adoption of SFAS 131 can help reduce information asymmetry between firms and their capital providers, improving the firm's access to sources of financing. Having better access to finance after the adoption of SFAS 131, these firms rely less on trade credit financing. Further analysis reveals that the adoption of SFAS 131 leads to a reduction in the firm's financial constraints, and stock illiquidity and an increase in equity issuance. Overall, we show that the adoption of SFAS 131 leads firms to substitute away from trade credit financing toward equity financing.

3.1 Introduction

There is an extensive literature on trade credit (e.g., Smith, 1987; Biais and Gollier, 1997; Petersen and Rajan, 1997; Fisman and Love, 2003; Love et al., 2007) which focuses on the importance of its use when traditional sources of financing (i.e., bank borrowing, bonds, and equity) are scarce. The information asymmetry between firms and their capital providers is one such important determinant of the availability of financing. As prior research shows, firms should rely more on sources of financing that are less information-sensitive when the level of information asymmetry is high (Leland and Pyle, 1977; Diamond, 1984; Houston and James, 1996; Denis and Mihov, 2003). In this vein, theoretical work on trade credit shows that firms are likely to rely more on trade credit when they have limited access to traditional financing sources, due to information asymmetry. This is because suppliers of these firms can have an informational advantage over traditional financial institutions in overcoming asymmetric information and moral hazard problems (e.g., Biais and Gollier, 1997; Burkart and Ellingsen, 2004).

Empirically, there has been some evidence supporting the argument that the use of trade credit is related to the suppliers' advantage over financial institutions in acquiring information about the credit quality of a firm. Prior empirical research (e.g., Chen et al., 2017; Chemmanur and Toscano, 2019; Li et al., 2021) shows that the use of trade credit can be driven by various aspects of the quality of firm information environment related to analysts coverage, accruals quality, and international financial reporting standards (IFRS). However, to the best of our knowledge, there has been no empirical study in the literature investigating the effect of exogenous changes in the information environment associated with the mandatory segment information disclosure on the firm's use of trade credit financing. The objective of our study is to fill this gap in the literature.

Corporate disclosures, particularly segment information disclosures, are likely to be an important source of information for capital market participants. The reporting of more disaggregated business segments is expected to facilitate capital market participants' understanding of the extent to which the firm is industrially diversified and enable them to evaluate the firm's individual segments' performance more thoroughly. Such disclosures can reduce the firm's information asymmetry concerning its diversification's actual co-insurance effect, allowing capital market participants to estimate and monitor the firm's credit risk more easily (Franco et al., 2016).[37] Previous theoretical work (e.g., Lewellen, 1971) suggests that industrial diversification provides a co-insurance effect that decreases the firm's default risk. By aggregating different industrial segments with imperfectly correlated earnings, a diversified firm can benefit from a co-insurance effect that reduces the variability of its overall earnings (Lewellen, 1971; Galai and Masulis, 1976) and helps avoid countercyclical deadweight costs (Hann et al., 2013).

Despite the importance of reporting more disaggregated segments to reduce information asymmetry between diversified firms and their market participants, the absence of mandatory adoption of segment disclosure induces some firms to provide low-quality segment disclosures (Franco et al., 2016). Specifically, the absence of such regulation induces some firms to withhold industry segment information if allowed to do so, which affects the quality of the segment disclosure (Berger and Hann, 2003).[38]

In June 1997, the Financial Accounting Standard Board (FASB) in the U.S. enacted new standards on segment reporting, namely the Statement of Financial Accounting Standards No. 131 (SFAS 131). Effective for fiscal years commencing after December 15, 1997, SFAS 131 required firms to provide information about their reportable business segments as defined for the firm's internal organisation. SFAS 131 was a response to financial analysts' long-standing complaints that the Statement of Financial Accounting Standards No. 14 (SFAS 14) allowed flexibility in defining reportable business segments. More specifically, SFAS 131 superseded the old standard (SFAS 14) that allowed managers to aggregate dissimilar business lines into broad industry segments, or even avoid providing segment disclosures at all (Knutson, 1993; AICPA, 1994; Pacter, 1993). Therefore, the new segment reporting standard (SFAS 131) can enhance the quality of segment disclosure by inducing managers to disclose previously "hidden" segment information, leading to a revision in capital market participants' beliefs about the firm's diversification activities. As noted by Berger and Hann (2003), some segment information was not

[37] Moody’s Investor Service rating methodology (Moody’s 2006) classifies the diversification of firm as one of the main factors driving credit ratings.

[38] According to Berger and Hann (2007), the reasoning behind withholding segment information is that managers tend to hide segments with low abnormal profits (from an agency cost motive perspective) or with high abnormal profits (from a proprietary cost motive perspective).

available to analysts prior to the reform, making the content of the new disclosures relevant to external investors.[39]

There are several existing studies on the implications of SFAS 131 adoption for firms' segment disclosure practices and information environments. They document a significant increase in the number of reported segments (Herrmann and Thomas, 2000; Berger and Hann, 2003; Ettredge et al., 2002), analysts' forecast accuracy (Venkataraman, 2001; Berger and Hann, 2003), the dispersion of segment profits (Ettredge et al., 2006), and stock price informativeness (Ettredge et al., 2005; Jayaraman and Wu, 2019). Given that these studies suggest that the adoption of SFAS 131 provides new information about a firm's diversification status, potential capital providers (e.g., debtholders and shareholders) may rely on this public information to evaluate the extent to which a firm is diversified across different business lines. Therefore, revealing new information about the firm's segments can alleviate a firm's external financial constraints and enhance its access to external capital markets. As noted by Franco et al. (2016), SFAS 131 decreases information asymmetry between diversified borrowing firms and their bondholders, which leads to a decline in the cost of debt. Therefore, in this study, by exploiting the change in U.S. segment reporting rules from SFAS 14 to SFAS 131, we examine the impact of exogenous changes in the information environment on a firm's use of trade credit as a financing choice. Our objective is to provide causal evidence on whether the increase in public information, due to the improvement in segment disclosure quality under SFAS 131, causes a change in the use of trade credit.

Why does the change in the firm's information environment caused by the adoption of SFAS 131 affect the use of trade credit? As mentioned earlier, the theoretical literature on trade credit (e.g., Smith, 1987; Brennan et al., 1988; Biais and Gollier, 1997) show that the asymmetry in the cost of assessing firms' creditworthiness is an important explanation for the existence of trade credit financing, as suppliers are in a better position than financial institutions to evaluate the creditworthiness of their customers. Informational advantage of suppliers is likely to arise because suppliers and their customers operate in closely related business lines. When there is information asymmetry between firms and financial institutions (e.g., banks), the

[39] Moreover, the adoption of SFAS 131 improves the transparency of capital allocations among business segments characterised by different opportunities, thereby improving the ability of shareholders to monitor managers (Cho, 2015).

latter is reluctant to be exclusive lenders because they may face a lemon problem which would result in an adverse selection of borrowers (Giannetti et al., 2011). Financial institutions are likely to become more inclined to lend if they observe that suppliers offer trade credit (Biais and Gollier, 1997). These arguments suggest that financial institutions may rely on suppliers' private information to make lending decisions when faced an adverse selection problem. However, if the adoption of SFAS 131 causes a decrease in the information asymmetry between firms and financial institutions, the information advantage of suppliers is expected to decrease. This is because financial institutions can use the newly revealed information about a firm's corporate diversification status to evaluate the firm's creditworthiness. It is expected that firms that revealed new information about their corporate diversification status would have better access to external financing, as the reporting of more disaggregated segments and segment-level information allows financial institutions to better assess the firm's credit risk (e.g., co-insurance effect). Thus, such firms are able to utilise traditional sources of financing rather than rely on the relatively more expensive trade credit. We, therefore, hypothesise that a firm's adoption of SFAS 131 could decrease the use of trade credit.

Despite the adoption of SFAS 131 being likely to reduce the use of trade credit, due to a reduction in the information asymmetry, SFAS 131 might, however, increase the use of trade credit. For example, if the adoption of SFAS 131 draws attention to inefficient cross-subsidization across segments that distort internal resource allocations, thereby reducing the firm value (e.g., Berger and Ofek, 1995; Rajan et al., 2000; Scharfstein and Stein, 2000), then firms are more likely to use more trade credit because they are likely to be more financially constrained. Nevertheless, this impact might be mitigated if diversified firms limit resource misallocations ex-ante, because they have committed to higher-quality segment disclosures under SFAS 131 that could expose these misallocations. The firms' adoption of SFAS 131 may also increase the use of trade credit due to proprietary costs if firms reveal more segment-specific information that is relevant to the firm's competitors (e.g., Nagarajan and Sridhar, 1996; Berger and Hann, 2003, 2007). Diversified firms' capital providers are likely to prefer their firms to provide more aggregated segment information to protect the firm's competitive advantage. Thus, capital providers might require a higher return if segment disclosures significantly increase proprietary costs (Berger and Hann, 2003; Franco et al., 2016). However, the firms' adoption of SFAS 131 may increase the use of trade credit, not because of disclosure costs, but because the newly revealed information under SFAS 131 is likely to be beneficial to suppliers. In particular, it is expected that suppliers, like other capital providers, face information asymmetry about their customers' creditworthiness, and they use segment information to assess their customers' credit risk. In such cases, the adoption of SFAS 131 is likely to induce suppliers to offer more trade credit to their customers.

To test our hypothesis, we conduct a difference-in-differences (DiD) research design that compares the effect of SFAS 131 on the use of trade credit (i.e., the ratio of accounts payable to total assets) of two groups of firms. The first group, which we call the treatment group (i.e., change firms), are firms that only disclosed a single segment before the adoption of SFAS 131 (i.e., they appeared as if they operated in a single industry) and were forced to reveal their previously hidden diversification status upon the adoption of SFAS 131. The second group, which constitutes the control group (i.e., no-change firms), refers to firms that disclosed a single segment before and after the adoption of SFAS 131.[40] This comparison between treatment and control groups is relevant to our research question because the single-to-multi-segment firms were pooled with the single segment firms prior to SFAS 131, by virtue of the single-to-multi-segment firms' decision to hide the industry segment information (Botosan and Stanford, 2005).

Using a sample of 392 change firms and 1,560 no-change firms over the period 1994–2002, we find a significant reduction in the use of trade credit after the adoption of SFAS 131. More specifically, we observe a 1.78 percentage points decrease in the use of trade credit for change firms relative to no-change firms. This decrease is of substantial economic magnitude. Comparing a 1.78 percentage points decrease in the use of trade credit to the sample average (9.4 percentage points), translates into an approximately 19% decrease. We derive these results after controlling for a range of firm characteristics, as well as the inclusion of firm and year fixed effects in the DiD model. In support of the parallel trends assumption, we find that changes in the use of trade credit of change firms and no-change firms prior to the adoption of SFAS 131 are, indeed, indistinguishable. Moreover, we perform

[40] We use the terms "single-to-multi-segment firms" "SM", and "change firms" to refer to treated firms and "single segment firms", "SS", and "no-change firms" to refer to control firms.

a placebo test to examine whether more disaggregated information at the segment level, rather than revealed diversification status, could explain the change in the use of trade credit. The placebo treatment group consists of firms that revealed an increased number of operating segments under the adoption of SFAS 131 while still operating in a single industry (i.e., firms that disaggregate segment data at the segment level but still operate in the same four-digit SIC code industry). We find no evidence of a decrease in the use of trade credit in the placebo group after the adoption of SFAS 131 relative to no-change firms.

Next, we conduct a variety of robustness checks on our main findings to assess the internal validity of our DiD results. First, the change versus no-change classification may be endogenous. Despite the mandatory nature of SFAS 131 adoption, the control group may contain firms that should have disclosed multiple segments under SFAS 131 but strategically decided to remain no-change firms (Cho, 2015). To deal with this concern, we replace our control group with another group of firms which are multi-segment firms that disclosed the same number of segments before and after the adoption of SFAS 131 (i.e., multi-segment firms whose reported segments were already consistent with SFAS 131). We find that our results are robust to an alternative group of control firms. Second, we undertake a propensity-score matched sample to control for underlying differences between change and no-change firms. We match change and no-change firms based on their propensity scores during the pre-SFAS 131 period and then perform the DiD estimation using the matched sample. Our results remain qualitatively similar. Third, the unobserved time-varying state-specific or industry-specific heterogeneity that may drive our results. To mitigate this concern, we control for state-year and industry-year interacted fixed effects. The results are robust, with statistical and economic significance comparable to our baseline findings. Fourth, our results are robust to different estimation windows. In particular, our results continue to hold if we use a window of three or five years before and after the adoption of SFAS 131. Finally, our results are robust to alternative ways of defining the use of trade credit.

Our results so far provide strong evidence that the improvement in segment disclosure under SFAS 131 reduces the use of trade credit. Findings support the idea that the adoption of SFAS 131 helps to reduce the information asymmetry between capital providers and diversified firms and, thereby, reduces the firms' reliance on trade credit financing. This result is consistent with the theoretical literature on trade credit (e.g., Smith, 1987; Brennan et al., 1988; Biais and Gollier, 1997), that its use increases (decreases) when information asymmetry is high (low). In order to further understand how a decline in the use of trade credit following the adoption of SFAS 131 is related to the decrease in a diversified firm's information asymmetry, we next present a battery of cross-section tests to reinforce the inference derived from the above baseline results. Specifically, we examine the moderating effects of ex-ante default risk, information opacity, corporate governance, and auditing quality, respectively.

The first cross-sectional analysis relates to the firms' ex-ante default risk. Prior research shows that suppliers offer more trade credit to their customers when information about their customers' default risk is asymmetrically held, as suppliers use trade credit as a screening device to identify the default risk of their customers (Smith, 1987). However, if the adoption of SFAS 131 provides new information to capital providers with respect to the co-insurance effect of diversification, which can reduce default risk (Lewellen, 1971), then firms with a higher default risk during the pre-SFAS 131 period would benefit more from the adoption of SFAS 131. This is because the adoption of SFAS 131 helps these firms to reduce capital providers' information asymmetry with respect to the firm's true diversification status. From the capital providers' perspective, the adoption of SFAS 131 makes it easier to evaluate the firm's credit risk, which in turn mitigates the firm's capital rationing. Therefore, if the decline in the use of trade credit after the adoption of SFAS 131 results from providing new information about the firm's actual co-insurance effect, then the negative impact of SFAS 131 on the use of trade credit would be greater for change firms with a higher default risk during the pre-SFAS 131 period. Consistent with this prediction, using the Ohlson (1980) O score and the Altman (1968) Z score as measures of ex-ante default risk, we find that the decrease in the use of trade credit is greater for change firms facing a greater default risk during the pre-SFAS 131 period.

The second cross-sectional analysis relates to the extent of information opacity of the firms. If SFAS 131 adoption presents capital providers with information that facilitates the effective monitoring of a firm's performance and credit risk (Ettredge et al., 2005; Franco et al., 2016), then firms with more opaque information environments in the pre-SFAS 131 period should benefit more. In particular, if the decline in the use of trade credit after the adoption of SFAS 131 results from the improvement in the information environment (Berger and Hann, 2003; Botosan and Stanford, 2005; Ettredge et al., 2005), then the negative impact of SFAS 131 on the use of trade credit is expected to be greater for change firms with greater information opacity during the pre-SFAS 131 period. Consistent with this prediction, using the probability of informed trading (PIN) and idiosyncratic risk (IR) as measures of information opacity, we find that the decrease in the use of trade credit is concentrated in change firms with a more opaque information environment during the pre-SFAS 131 period.

The third cross-sectional analysis relates to the firms' corporate governance quality. Prior research (e.g., Harris and Raviv, 2008; Duchin et al., 2010) suggests that firms with weak governance are associated with higher information asymmetry and monitoring costs. If the adoption of SFAS 131 improves the firm's information environment, then firms with weak governance during the pre-SFAS 131 period would benefit more from the adoption of SFAS 131. This is because firms with weak governance have more limited access to sources of financing and resort to their suppliers for trade credit, while the adoption of SFAS 131 improves these firms' access to finance by reducing information asymmetry and monitoring costs. Thus, we expect firms with weaker governance during the pre-SFAS 131 period to be more affected by the adoption of SFAS 131. Consistent with this idea, using institutional ownership and takeover threats as measures of corporate governance, we find that the decrease in the use of trade credit is greater for change firms with weak governance during the pre-SFAS 131 period.

The final cross-sectional analysis we conduct focuses on the quality of the auditors of the firms. The rationale behind this test relies on the idea that firms audited by Big 4 audit firms in the pre-SFAS 131 period may have already generated credible financial reporting that reduces information asymmetry between firms and their capital providers and, thereby, allowed the latter to better evaluate the performance of these firms. Thus, firms audited by Big 4 auditors may benefit less from the adoption of SFAS 131. In contrast, firms audited by non-Big 4 auditors are expected to benefit more from the adoption of SFAS 131, because they may be subject to relatively less auditor scrutiny and consequently have lower financial reporting quality and having higher information asymmetry. Thus, we expect firms audited by non-Big 4 auditors in the pre-SFAS 131 period to be more affected by the adoption of SFAS 131. Consistent with this idea, we find that the negative effect of SFAS

131 on the use of trade credit is greater for change firms that were audited by non-Big 4 audit firms during the pre-SFAS 131 period.

Collectively, the evidence suggests that the decrease in the use of trade credit stems from the firm's improved information environment after the adoption of SFAS 131, which allows firms to rely less on trade credit and have better access to other sources of financing. As further evidence in support of this mechanism, we directly examine the impact of the adoption of SFAS 131 on financial constraints, stock illiquidity and equity and debt issuances. We find a significant reduction in financial constraints and stock illiquidity for change firms after the adoption of SFAS 131. Moreover, we find that change firms tend to issue more equity after the adoption of SFAS 131. This finding suggests that the adoption of SFAS 131 provides equity investors with better information about the firm's diversification activities, which in turn eases financial constraints and facilitates equity financing.

Our study contributes to two strands of literature. First, it adds to the literature that examines the use of trade credit when access to sources of financing is limited. Previous studies on trade credit (e.g., Nilsen, 2002; Love et al., 2007; Garcia-Appendini and Montoriol-Garriga, 2013) focus on its use when firms suffer from temporary liquidity shocks or monetary tightening. Abdulla et al. (2017) and Shang (2020) examine the access to the equity capital market and the use of trade credit. Existing empirical studies (e.g., Petersen and Rajan, 1997; Chen et al., 2017; Chemmanur and Toscano, 2019; Li et al., 2021) also examine whether the use of trade credit substitutes for other financing sources in presence of information asymmetry. Our study complements this literature by providing evidence that segment disclosure could reduce information asymmetry and decrease the use of trade credit. Specifically, our study contributes to a strand of literature that examines the link between the change in a firm's information environment and the use of trade credit. While Chen et al. (2017) examine the impact of accounting quality (i.e., accruals quality), Li et al. (2021) investigate the impact of international financial reporting standards (IFRS), and Chemmanur and Toscano (2019) examine the impact of analyst coverage, our study concentrates on a specific source of information, namely, segment information disclosure that is value-relevant and informative to capital market participants. Our evidence suggests that segment disclosures may help capital market participants to evaluate the extent to which a firm is diversified across different business lines and the firm's credit risk, which ultimately drives the use of trade credit.

Second, our study adds to the growing literature on the economic consequences of the mandatory adoption of SFAS 131. While prior studies in finance and accounting examine various implications of SFAS 131 adoption and segment disclosure, no study has examined the impact of this reform on the use of trade credit. Herrmann and Thomas (2000) show that the adoption of SFAS 131 reveals more detailed segmentation, which leads to a reduction in the number of single-segment firms. Cho (2015) examines the impact of SFAS 131 on the efficiency of internal capital markets. Berger and Hann (2003) investigate the effect of SFAS 131 on stock prices and find that the diversification discount for these previously "hidden" diversified firms increases in the post-SFAS 131 period. Jayaraman and Wu (2019) show that SFAS 131 discourages informed trading and, thereby, reduces stock price informativeness. Franco et al. (2016) show that SFAS 131 reduces the cost of debt. Our study contributes to this stream of research by showing that the adoption of SFAS 131 could have a significant effect on the use of trade credit as a source of financing.

The remainder of the chapter is organised as follows. Section 3.2 discusses the related literature and develops our hypotheses. Section 3.3 discusses the data and sample selection, and the research design is explained in Section 3.4. Empirical results are reported in Section 3.5, which is followed by a conclusion in Section 3.6.

3.2 Literature Review and Hypothesis Development

This section provides a brief review of the existing empirical literature that is most relevant to our study, followed by a discussion of the development of our hypotheses, corresponding to the research questions outlined in our introduction.

3.2.1 Related Literature

In this subsection, we review the literature on trade credit and segment disclosures, emphasizing those papers that are most relevant to our study.

3.2.1.1 Literature on Trade Credit

The literature on trade credit suggests that one of the most important explanations for the use of trade credit is the financing motive (e.g., Schwartz, 1974). Trade credit is available to firms that have limited access to external sources of financing (i.e., bank borrowing, bonds, and equity) because trade creditors have a financing advantage over traditional financial institutions in investigating the creditworthiness of their customers, as well as a better ability to monitor and force repayment of the credit (Schwartz, 1974; Emery, 1984; Mian and Smith, 1992; Petersen and Rajan, 1997). Closely related to this current study is a stream of literature that emphasizes the importance of the use of trade credit when firms are not able to access other sources of financing due to asymmetric information. A widespread view in the trade credit literature (e.g., Schwartz and Whitcomb, 1979; Ferris, 1981; Emery, 1984; Mian and Smith, 1994; Jain, 2001) is that suppliers have an informational advantage over traditional financial institutions. Specifically, suppliers have private information about their customers as a by-product of the selling activities, while financial institutions can only acquire such information at a cost. Several theories of trade credit have been built on this view to explain the use of trade credit. Bias and Gollier (1997) and Smith (1987) point out that the asymmetry in the cost of assessing a firm's creditworthiness explains the existence of the use of trade credit, because suppliers are in a better position than financial institutions to assess the creditworthiness of firms with greater information asymmetry.

There is a large body of empirical literature that examines links between the financing motive and the informational advantage of trade creditors in particular, and the use of trade credit. For example, Petersen and Rajan (1997) find that small firms tend to use more trade credit when bank credit is rationed. Nilsen (2002), Love et al. (2007), Garcia-Appendini and Montoriol-Garriga (2013), and Carbo-Valverde et al. (2016) show that trade credit increases following a monetary contraction. Previous studies also examine the effect of equity market financing on the use of trade credit. Abdulla et al. (2017) find that private firms are more reliant on trade credit than their public counterparts, as public firms have better access to sources of financing.[41] Shang (2020) shows that equity market characteristics, such as stock

[41] In fact, Abdulla et al. (2017) point out that private firms have higher information asymmetry than public firms, which induces private firms to resort more to trade credit, as suppliers have an informational advantage over financial institutions.

liquidity, also affect public firms' use of trade credit. In particular, he finds that public firms with higher stock liquidity are less reliant on trade credit financing.

More closely related to the informational advantage of suppliers, Chen et al. (2017) and Chemmanur and Toscano (2019) find that the use of trade credit increases when information asymmetry between firms and their capital providers is high. In particular, Chemmanur and Toscano (2019) show that firms increase their use of trade credit following reductions in analyst coverage (i.e., after brokerage house mergers). Chen et al. (2017) investigate another source of information production that is likely to affect the use of trade credit. In particular, they show that firms with low accounting quality use more trade credit. This is because firms with low accounting quality have high information asymmetry and, thereby, have limited access to sources of financing. In contrast, Li et al. (2021) find in a cross-country study that the use of trade credit increases when information asymmetry is low. More specifically, they show that firms in countries that adopt international financial reporting standards (IFRS) receive more trade credit from their suppliers. They argue that after the adoption of IFRS, the improvement in financial reporting quality and comparability plays a role in facilitating supplier financing.[42]

Overall, the extant literature provides useful insights into the importance of trade credit financing when the firm's information asymmetry is high. However, to the best of our knowledge, there has been no study in the literature investigating the effect of the exogenous change in firm information environment associated with segment information disclosure on the firm's use of trade credit financing. This is an important gap in the trade credit literature because existing studies on segment disclosure (e.g., Herrmann and Thomas, 2000; Berger and Hann, 2003; Ettredge et al., 2005; Jayaraman and Wu, 2019) show that improvement in segment disclosure quality plays an important role in mitigating information asymmetry between firms and their market participants. Our study differs from previous studies on the relationship between information environment and trade credit, as we focus on the effect of the disclosure of segment information. This such disclosure is value-

[42] Li et al. (2021) argue that, although having an information advantage, suppliers could face information asymmetry from their customers and the adoption of IFRS enhanced financial reporting quality and comparability which have a positive effect on trade credit. The rational behinds this relationship is that suppliers' information advantage is mainly valid for local supplier-customer relationships. In an international setting, suppliers often trade with foreign customers, and, thus, suppliers' information advantage is likely to be difficult to acquire. Moreover, they argue that suppliers need information from financial statements to assess the risks of their customers.

relevant and particularly useful for capital market participants in assessing firms' credit risk. Thus. it is likely to be an important determinant of the use of trade credit.

3.2.1.2 Literature on Segment Disclosures

Researchers have argued for a link between corporate disclosure and information asymmetry (e.g., Diamond and Verrecchia, 1991; Botosan, 1997; Leuz and Verrecchia, 2000; Healy et al., 2001). Specifically, an increase in disclosure level can reduce the adverse selection problem in the presence of information asymmetry between firms and capital market participants. Revealing public information to reduce information asymmetry is expected to attract increased demand from investors, which, in turn, helps firms to lower their cost of capital (Diamond and Verrecchia, 1991). In this vein, prior studies have examined the economic consequences of segment disclosure. They show that the industry segment disclosures furnished by firms in compliance with SFAS 14 reporting requirements improve security valuation (Kinney 1971; Collins and Simonds 1979; Tse, 1989) and enhance analysts' earnings forecasts (Kinney, 1971; Collins, 1976; Baldwin, 1984; Swaminathan, 1991). Similarly, Botosan and Harris (2000) show that firms are more likely to voluntarily increase the frequency of their segment disclosures following declines in their liquidity and analyst forecast consensus, presumably to reduce information asymmetry among capital market participants. This literature generally suggests that the information provided by segment disclosures under SFAS 14 is useful to capital market participants.

Firm segment disclosures can be an important source of information for capital market participants. This is because segment disclosures may facilitate capital market participants' understanding of the extent to which a firm is industrially diversified and enable them to evaluate the firm's individual segments' performance more thoroughly. More importantly, such disclosures can reduce the firm's information asymmetry with respect to its diversification's actual co-insurance effect, allowing capital market participants to estimate the firm's credit risk more accurately (Franco et al., 2016). The early theoretical work on corporate diversification suggests that diversification can provide a co-insurance effect by aggregating different business segments with imperfectly correlated segment cash flows (e.g., Lewellen, 1971; Higgins and Schall, 1975; Galai and Masulis, 1976). This co-insurance effect helps the diversified firm lower the volatility of its overall earnings and default risk. Moreover, the co-insurance effect enables diversified firms to avoid the countercyclical deadweight costs of financial distress, which leads to a reduction in systematic risk (Hann et al., 2013; Franco et al., 2016).[43] These arguments suggest that capital market participants can use the information provided by firms' segment disclosure to assess the co-insurance effect of a firm's industrial diversification. Thus, segment disclosures are a valuable source of information for capital market participants to assess firms' credit risk.

Although firms' segment disclosure is important to mitigate information asymmetry between diversified firms and the market participants, the absence of mandatory regulation of segment disclosures induces some firms to provide low-quality segment disclosures (Franco et al., 2016). More specifically, some firms withhold industry segment information if allowed to do so, which affects the quality of segment reporting (Berger and Hann, 2003). Financial analysts and other users of segment reports have maintained that SFAS 14 was inadequate (Knutson, 1993). Although encouraged, disclosure of segment information is not compulsory under SFAS 14 (Botosan and Stanford, 2005). The Association for Investment Management and Research (AIMR) and the American Institute of Certified Public Accountants (AICPA) claimed the need for a new business segment standard because firms disclosed segment data on a voluntary basis under SFAS 14 (Knutson, 1993; AICPA, 1994). As documented by Botosan and Harris (2000), who study a sample of multi-segment firms over the period 1987-1994, about 60% of their sample firms disclose segment data voluntarily, while the remaining 40% disclose no segment data. Therefore, financial analysts' complaints may stem from extremely poor disclosures by some firms which needed to improve their segment reports.[44]

After extensive lobbying by analysts and other users of financial reports, the Financial Accounting Standard Board (FASB) issued SFAS 131 in June 1997, which

[43] There are empirical studies that have established a link between corporate diversification and the cost of capital. For example, Hann et al. (2013) find that diversified firms have a lower cost of debt and cost of equity than comparable portfolios of standalone firms. Aivazian et al. (2015) find that diversified firms have lower loan rates than their standalone counterparts. The negative impact of corporate diversification on the cost of capital results from the imperfect correlation of business units' cash flows, which can reduce systematic risk through the avoidance of countercyclical deadweight costs (Lewellen, 1971; Hann et al., 2013).

[44] The improvements requested in segment disclosures included: (1) a greater number of segments for some firms, (2) more information about segments, (3) consistency of segment information with the information provided in other parts of the annual report, and (4) a segment definition that aligned with internal management reports (Botosan and Harris, 2000).

became effective and mandatory for all public U.S. firms for fiscal years commencing after December 15, 1997. An important distinction between SFAS 14 and SFAS 131 is the definition of a segment. In particular, under SFAS 14, firms were required to classify line-of-business segment information using the industry approach.[45] A major concern with SFAS 14 was that discretion in the definition of segments allowed many firms to report much less segment information to outsiders than was reported internally (Ernst and Young, 1998; Berger and Hann, 2003). However, under SFAS 131, firms are required to classify line-of-business segment information using the management approach. The management approach requires disaggregated information to be presented based on how management internally evaluates the operating performance of its business units (Berger and Hann, 2003). This new standard induces firms to provide more disaggregated information, which helps external investors evaluate segment units based on how management organises segments within the firm for making decisions and assessing performance.[46] Therefore, the new segment reporting standard (SFAS 131) can enhance the quality of segment disclosure by inducing managers to disclose previously "hidden" segment information, which can lead to a revision in capital market participants' beliefs about a firm's diversification activities.

There is a consensus in the segment disclosure literature that the adoption of SFAS 131 improves the transparency of segment information and firms' information environment, as well as enhances the monitoring environment (e.g., Berger and Hann, 2003; Ettredge et al., 2005; Cho, 2015). Previous studies document that the adoption of SFAS 131 induced firms to increase the number of reported segments (Herrmann and Thomas, 2000; Berger and Hann, 2003; Ettredge et al., 2002). Consistent with the improvement in a firm's information environment, the literature shows that the adoption of SFAS 131 improved analysts' forecast accuracy, because SFAS 131 enabled analysts to access information previously hidden under SFAS 14 and, thereby, forecast firms' future performance more accurately (Venkataraman, 2001; Berger and Hann, 2003). Moreover, the adoption of SFAS 131 increased analysts' reliance on public information (Botosan and Stanford, 2005). The adoption

[45] This approach allows managers to report more aggregated segment information to market participants than what is reported internally (Berger and Hann, 2003).

[46] An example given by Berger and Hann (2003) is IBM, one of the firms that restated its segment report from one industry segment under SFAS 14 to seven operating segments under SFAS 131.

of SFAS 131 also increased stock price informativeness (Ettredge et al., 2005; Jayaraman and Wu, 2019). The literature also shows that the improvement in segment disclosure quality under SFAS 131 facilitates the monitoring role of outside investors. For instance, Berger and Hann (2003) find that firms reported as single-segment firms under SFAS 14, but as multi-segment firms under SFAS 131, suffered a value decrease upon adoption of SFAS 131. This indicates that SFAS 131 revealed agency problems associated with the internal capital markets of diversified firms that were previously hidden under SFAS 14. Cho (2015) shows that the adoption of SFAS 131 improves the transparency of capital allocations across segments characterised by different opportunities, which, in turn, improves shareholders' ability to monitor managers.

Although the existing literature has examined the economic consequences of SFAS 131 adoption, few studies have investigated this regulatory change from the perspective of corporate financing policy. Looking at the cost of debt, Chen and Liao (2015) and Franco et al. (2016) show that SFAS 131 lowers bond yields because SFAS 131 can improve the segment disclosure quality and thereby reduce the information asymmetry between firms and their bondholders by providing information on the co-insurance effect. Moreover, Akins (2018) finds that the adoption of SFAS 131 lowers uncertainty regarding credit risk as captured by disagreement among credit rating agencies. Altieri (2020) shows that firms reported as single-segment before SFAS 131 but as multi-segment after SFAS 131 suffered an increase in the yield spreads. This is because SFAS 131 draws attention to inefficient cross-subsidization across segments that distorts internal resource allocations and leads to firm-wide losses, which induces bondholders to require higher bond yields. Our study adds to this growing strand of research by examining an alternative financing channel; namely, trade credit financing. In particular, by exploiting the change in segment reporting quality under SFAS 131, our study investigates how exogenous changes in the information environment affect a firm’s use of trade credit financing, which is an important source of short-term financing. In the next subsection, we formally develop our testable hypotheses.

3.2.2 Hypothesis Development

Based on the different strands of literature reviewed above, we develop our hypotheses regarding the effect of an exogenous change in the firm's information environment, associated with the mandatory segment information disclosure, on the firm's use of trade credit financing. The trade credit literature (e.g., Smith, 1987; Brennan et al., 1988; Biais and Gollier, 1997; Petersen and Rajan, 1997; Burkart and Ellingsen, 2004) suggests that firms resort to trade credit when access to traditional sources of financing is limited. Under the assumption that trade credit is more expensive than institutional finance (e.g., bank credit), firms typically prefer to finance themselves through cheaper institutional finance when access to such a source is relatively unrestricted (e.g., Ng et al., 1999; Petersen and Rajan, 1997; Wilner, 2000). However, when access to institutional finance is restricted, firms need to complement their financing with trade credit. According to the literature, suppliers are willing to extend trade credit to firms with limited access to traditional sources of financing because suppliers have an informational advantage over financial institutions in overcoming asymmetric information and moral hazard problems (e.g., Smith, 1987; Brennan et al., 1988; Biais and Gollier, 1997). This informational advantage partly stems from the fact that suppliers visit their customers' premises more often than financial institutions would. Moreover, the size and timing of their customers' orders give suppliers a signal of the condition of the customers' business (Petersen and Rajan, 1997, Smith, 1987). Financial institutions might also get similar information, but suppliers are able to get the information about their customers faster and at a lower cost because they obtain it in the ordinary course of business (Petersen and Rajan, 1997). Therefore, suppliers have an informational advantage in the sense that they often have private information about their customers that financial institutions may not have (Biais and Gollier, 1997).

There has been a concerted effort by the theoretical literature on trade credit to explain the relationship between information asymmetry and the use of trade credit. For example, Biais and Gollier (1997) develop a theoretical model assuming that there is information asymmetry between firms and banks about firms' creditworthiness. They show that there are two types of firms. Some are "good", with positive net present value (NPV) projects. Other firms (the "bad") have negative NPV projects. The firms privately know their type, while suppliers and banks only have different signals about the type of their borrowing firms. When bank credit is the only source of financing, if the proportion of “bad” firms is large and there is information asymmetry between bank and firms, then all firms, including the "good" and the “bad”, are denied credit. This prevents “good” firms from investing in positive NPV projects (i.e., market breakdown due to information asymmetry). In such cases, suppliers which have private information about their customers' creditworthiness can play an important role in conveying their private information to banks by extending trade credit to their customers. As a result, banks may become more willing to lend to the firms that receive trade credit from suppliers. These arguments suggest that financial institutions may rely on suppliers' private information to lend to their borrowing firms in the existence of an adverse selection problem.[47]

In the above setting, we incorporate the role of segment information disclosure mandated by SFAS 131 in mitigating the asymmetric information problems facing capital market participants. As mentioned earlier, the literature on segment disclosure shows that SFAS 131 enhances the quality of segment disclosures by forcing firms to disclose previously "hidden" segment information (e.g., Herrmann and Thomas, 2000; Street et al., 2000; Berger and Hann, 2003, 2007; Ettredge et al., 2005). Given that the adoption of SFAS 131 provides new information about a firm's diversification status, potential capital providers (e.g., banks, bondholders, and shareholders) can use this public information to evaluate the extent to which a firm is diversified across different business lines. Therefore, revealing new information about the firm's segments can improve its access to traditional sources of financing. As documented by Franco et al. (2016), SFAS 131 plays an important role in mitigating information asymmetry between diversified borrowing firms and their bondholders, which reduces the cost of debt. More specifically, the disclosure of

[47] Biais and Gollier (1997) assume that the use of trade credit can facilitate aggregation of the supplier's information with the financial institution’s information and, thus, reduce information asymmetry and adverse selection. This might also induce the financial institutions themselves to lend to the customers, because suppliers convey positive information about the customer to the financial institutions. However, this motivation (conveying positive information about the customer to the financial institutions) is only if the main driving force behind the extension of trade credit is the precision of the pooled information of suppliers over financial institutions. It may be that there are several motivations that lead suppliers to extend trade credit to their customers suffering from credit rationing, such as price discrimination and transaction cost motivations (see Section 2.2.1 for more details). In this study, we do not concentrate on the signaling role of trade credit extension; rather, we focus on whether the firms decide to use less to trade credit when their capital providers obtain more information about them from the market, not from suppliers.

more disaggregated segments and segment-level information allows capital providers to better assess a firm's co-insurance effect of diversification and its credit risk. To the extent that the adoption of SFAS 131 reduces the information asymmetry between firms and capital providers, the information advantage of suppliers relative to traditional capital providers diminishes.

Consequently, firms that reveal new information about their corporate diversification status under SFAS 131 are able to utilise traditional sources of financing rather than the more expensive trade credit. Thus, the adoption of SFAS 131 could decrease a firm’s use of trade credit. To test this conjecture, we examine the effect of SFAS 131 on a group of treatment firms (i.e., “change firms” which are diversified firms reported as single segment firms before SFAS 131 and forced to reveal their previously hidden diversification status after SFAS 131), using the standalone firms pre- and post-SFAS 131 (i.e., "no-change firms") as the control group. Our first hypothesis stated as follows:

H1: *Change firms (i.e., treatment group) experience a greater reduction in the use of trade credit in the post-SFAS 131 period relative to the pre-SFAS 131 period than no-change firms (i.e., control group).*

In contrast, a firm's adoption of SFAS 131 is expected to lead to an increase in the use of trade credit for several reasons. First, the adoption of SFAS 131 may reveal a particular type of agency problem, namely inefficient cross-subsidization between divisions (Berger and Hann, 2003). Prior research on corporate diversification (e.g., Berger and Ofek, 1995; Scharfstein, 1998; Shin and Stulz, 1998; Rajan et al., 2000; Scharfstein and Stein, 2000; Lamont and Polk, 2002) shows that managers of diversified firms who have discretion on internal resource allocations may allow resources to flow toward underperforming divisions, leading to inefficient investments and a loss in firm value. Thus, if the adoption of SFAS 131 reveals such agency problems, capital providers would be reluctant to provide funding, which, in turn, induces firms to rely on trade credit. However, this effect on the use of trade credit is not straightforward. Firms are expected to limit resource misallocations ex-ante by committing to higher-quality segment disclosures under SFAS 131, which could expose these misallocations. As documented by Cho (2015), diversified firms that improved segment disclosure transparency by changing segment definitions upon adoption of SFAS 131 experienced an improvement in capital allocation efficiency in internal capital markets.

Second, the adoption of SFAS 131 may increase the use of trade credit, due to proprietary costs associated with the adoption of SFAS 131. In particular, the adoption of SFAS 131 reveals proprietary information by disclosing relevant information to competitors (Berger and Hann, 2007), which negatively affects the firm's long-term performance (Nagarajan and Sridhar, 1996; Harris, 1998). Botosan and Stanford (2005) show that firms use the latitude in SFAS 14 to withhold profitable segments operating in less competitive industries than their primary operations. In such cases, capital providers may prefer diversified firms to hide segment information to protect the firm's competitive advantage. Thus, capital providers are likely to require higher returns if the adoption of SFAS 131 increases proprietary costs, increasing the firm's reliance on trade credit.[48]

Third, the adoption of SFAS 131 may increase the use of trade credit because of the new information provided to suppliers. In particular, despite having private information about customer firms, suppliers, like other capital providers, may face difficulties in estimating their customers' demands and evaluating their credit risk accurately. For example, CIT Group Inc and other factoring agents decided to stop financing Sear's sales due to concerns about Sear's financial problems. These suppliers were reluctant to provide trade credit to Sears because they could not evaluate the value of Sears's assets due to limited access to its financial information (Zimmerman and Eder, 2012; Chen et al., 2017). As such, the adoption of SFAS 131 could also help suppliers better assess their customer credit risk, and consequently, suppliers may offer more trade credit to the firms that revealed their previously hidden diversification status under SFAS 131.

Recall our main hypothesis, "H1", that change firms are able to reduce the use of trade credit due to the improvement in firm information environment associated with the segment information disclosure under SFAS 131, such an improvement in the information environment would be more important for firms that are financially distressed and informationally opaque before the adoption of SFAS 131. We, therefore, consider the cross-sectional variations in the effects of SFAS 131.

[48] We rely primarily on Franco et al. (2016) to build these arguments that work against our first hypothesis. In particular, Franco et al. (2016) argue that higher-quality segment disclosures can contribute to a lower cost of debt if they help to reduce bondholders' information asymmetry with respect to the co-insurance effect. On the other hand, they argue that if agency and proprietary costs associated with high-quality segment disclosures prevail over the co-insurance benefits of diversification, bondholders' are likely to require these firms to pay higher debt yields.

First, the effect of SFAS 131 on the use of trade credit varies with the level of default risk facing the firms during the pre-SFAS 131 period. In the presence of information asymmetry between distressed firms and capital market participants, suppliers are relatively more willing to provide trade credit to these firms as they can identify prospective defaults more quickly than financial institutions. Typically, suppliers have the incentive to offer trade credit to firms as a screening device that elicits information about customer default risk. This is also true in cases where suppliers have made non-salvageable investments in their customers, which enables them to take actions to protect such investments (Smith, 1987).[49] However, if the adoption of SFAS 131 provides new information to capital market participants, then firms with high ex-ante default risk would benefit more from the adoption of SFAS 131. This is because the co-insurance effect of diversification can mitigate capital providers' concerns about default risk. In particular, the mandatory segment information disclosure under SFAS 131 can reduce information asymmetry with respect to a firm's underlying diversification status, allowing capital market participants to evaluate and monitor the firm's credit risk more easily and, thereby, reducing capital rationing (Franco et al., 2016). Therefore, to the extent that the reduction in the use of trade credit is a result of a reduction in information asymmetry with respect to the co-insurance effect provided by the firm's true underlying diversification, the impact of SFAS 131 should be greater for change firms with a higher default risk during the pre-SFAS 131 period. This hypothesis is stated as follows:

H2*: The reduction in the use of trade credit, as stated in H1, is greater for change firms that suffered more severe default risk during the pre-SFAS 131 period than for other change firms.*

Second, the effect of SFAS 131 on the use of trade credit varies with the level of information opacity of firms during the pre-SFAS 131 period. Given that SFAS 131 reduces information asymmetry between firms and their capital market participants, we expect that SFAS 131 could provide countervailing benefits to firms with a more opaque information environment in the pre-SFAS 131 period. Under the assumption that SFAS 131 presents capital providers with information benefits that are valuable

[49] In fact, Smith (1987) argues that the high implicit interest rates that accompany trade credit facilitate the sorting of low, from high, default risk customers. See Section 2.2 for more details.

for more accurate estimation and effective monitoring of a firm's performance and credit risk (Ettredge et al., 2005; Franco et al., 2016), then firms with higher information opacity in the pre-SFAS 131 period should benefit more. This benefit results from the fact that the adoption of SFAS 131 makes these firms informationally less opaque, thereby improving their access to other cheaper sources of financing. Therefore, if a decline in the use of trade credit after the adoption of SFAS 131 results from the improvement in the information environment or the reduction in the firm's information asymmetry (Berger and Hann, 2003; Botosan and Stanford, 2005; Ettredge et al., 2005), then the negative impact of SFAS 131 on the use of trade credit is expected to be greater for change firms with a more opaque information environment during the pre-SFAS 131 period. This hypothesis is stated as follows:

H3: *The reduction in the use of trade credit, as stated in H1, is greater for change firms that suffered from a more opaque information environment during the pre-SFAS 131 period than for other change firms.*

Third, corporate governance mechanisms can affect the firm information environment, and, thus, the effect of SFAS 131 may vary with the corporate governance quality. More specifically, we expect the impact of SFAS 131 to be more pronounced for firms with weaker governance during the pre-SFAS 131 period. A large strand of the literature suggests that firms with weaker governance are associated with greater information asymmetry due to the high monitoring costs (Demsetz and Lehn, 1985; Chiang and Venkatesh, 1988; Hermalin and Weisbach, 1998; Raheja, 2005; Duchin et al., 2010). In contrast, firms with good governance are associated with better monitoring and higher information quality (Boone and White, 2015). Therefore, if the adoption of SFAS 131 improves the firm's information environment, then it is more beneficial for firms with weak governance. We thus expect that the negative impact of SFAS 131 on trade credit is greater for change firms with weak governance during the pre-SFAS 131 period. This hypothesis is stated as follows:

H4: *The reduction in the use of trade credit, as stated in H1, is greater for change firms with weak governance during the pre-SFAS 131 period than for other change firms.*

Finally, the quality of the firm’s external auditing can affect the firm information environment, and, thus, the effect of SFAS 131 may vary with the auditing quality.

In particular, we expect the impact of SFAS 131 to be greater for firms that are not audited by Big 4 audit firms during the pre-SFAS 131 period. Prior research (e.g., Raman and Wilson, 1994; Teoh and Wong, 1993; Khurana and Raman, 2004) shows that the four largest international accounting firms (i.e., Ernst & Young, Deloitte, KPMG, and PricewaterhouseCoopers) are perceived as providing higher quality audits, making financial reporting more credible, relative to other audit firms (i.e., non-Big 4 audit firms). The credible financial reporting under the scrutiny of Big 4 auditors can help reduce information asymmetry between firms and capital market participants, which in turn enhances investor confidence, raises the stock price and reduces the cost of capital (Khurana and Raman, 2004). It is expected that the adoption of SFAS 131 would be more beneficial for firms that are not audited by Big 4 auditors during the pre-SFAS 131 period because these firms may provide less credible financial information and consequently suffer from greater information asymmetry between the firms and their capital providers. Therefore, if a decline in the use of trade credit after the adoption of SFAS 131 results from the improvement in the information environment, then the negative impact of SFAS 131 on the use of trade credit is expected to be greater for change firms audited by non-Big 4 auditors during the pre-SFAS 131 period. This hypothesis is stated as follows:

H5: *The reduction in the use of trade credit, as stated in H1, is greater for change firms that were audited by non-Big 4 auditors during the pre-SFAS 131 period than for other change firms.*

3.3 Data and Sample Selection

Our sample is obtained from several sources: accounting data from Compustat, stock price data from CRSP, probability of informed trading (PIN) data from Brown et al. (2004), institutional ownership data from Thomson Reuters Institutional Holdings (13F) database, entrenchment index from Bebchuk et al. (2009), and segment data from the Historical Segments file of Compustat. We begin the sample construction with U.S. firms with business segment information (i.e., segment type "BUSSEG") during the period 1994-2002 (four years before and four years after the adoption of SFAS 131).[50] From this database, we classify firms as being either

[50] Because the adoption of SFAS 131 was effective for firms with fiscal years beginning after December 15, 1997, firms with December year-end adopted this regulation in 1998, whereas firms with non-December year-end adopted this regulation in 1999. Thus, for firms with December year-

change or no-change firms. Change firms are those that disclosed a single segment (i.e., disclosed single four-digit SIC code industry) prior to the adoption of SFAS 131 and were forced to reveal their previously hidden diversification status upon the adoption of SFAS 131 (i.e., they disclosed two or more different four-digit SIC code industries). No-change firms are defined as those that are standalone firms (i.e., disclose a single segment) in both pre-and post-adoption period of SFAS 131. We exclude financial firms (SIC codes 6000-6999), utilities (SIC codes 4900-4999), and government agencies (SIC codes 9000-9999). We further drop firm- and segment-year observations with missing segment SIC codes. We then obtain an initial sample of 14,917 firm-year observations with 2,570 unique firms including 737 change firms and 1833 no-change firms.[51]

Nevertheless, the change firm sample may contain firms that revealed their diversification status for reasons not related to the adoption of SFAS 131. In particular, there are change firms in the sample that are contaminated by events other than pure reporting changes (e.g., pooling acquisition, divestiture, restructuring, discontinued operations, or changes in accounting methods) (Berger and Hann, 2003; Cho, 2015). To ensure that the change firm sample captures only changes related to the adoption of SFAS 131, we exclude firms with concurrent changes in firm fundamentals.[52] This procedure reduces the sample to 13,604 firm-years with 2,269 unique firms (436 change firms and 1833 no-change firms).

Finally, we require firms to have valid information about total assets, sales, cost of goods sold and accounts payable, and we drop observations when these variables have negative values or when accounts payable exceeds the total book value of assets. We further require firms to have at least one observation in both pre-and post-SFAS 131 (this screen follows prior studies (e.g., Ettredge et al., 2005)).

end, the pre-SFAS 131 period covers 1994-1997, and the post-SFAS 131 period covers 1998 -2001. For firms with non-December year-end, the pre-SFAS 131 period covers 1995-1998, and the post-SFAS 131 period covers 1999 and 2002.

[51] Prior research (e.g., Berger and Ofek, 1995) argues that sales are usually completely allocated among the reported segments of a diversified firm; thus, the sum of segment sales must be within 1% of total sales for the firm. As a robustness check, we make our change firms satisfies this requirement (see Table 3.A3 in the Appendix).

[52] To do so, the prior research (e.g., Berger and Hann, 2003; Cho, 2015) uses an algorithm that allows distinguishing the effect of the revealed diversification from other changes in the adoption year. This algorithm compares the sums of segment sales between the restated data (hand collected data) from the first 10K reported under SFAS 131 and the old segment reports and considers firms as contaminated if the difference between old and restated sums differs by more than 1% of the restated sum. We thank Young-Jun Cho for sharing his list of firms with pure reporting changes related to the adoption of SFAS 131.

Furthermore, to eliminate outliers, all continuous variables used in our study are winsorized at the 1^{st} and 99^{th} percentiles. Our final sample consists of 12,174 firm-year observations with 1,952 unique firms (392 change firms and 1,560 no-change firms).

3.4 Research Design

To isolate the effect of SFAS 131 on the use of trade credit, we undertake a difference-in-differences approach that compares changes in the use of trade credit before and after the adoption of SFAS 131 for change firms (i.e., treated firms) as compared to no-change firms (i.e., control firms). We begin our regression analysis by controlling for the industry fixed effects using the Fama–French 48 industry classifications to control for unobserved industry heterogeneity. Also, we control for year fixed effects to mitigate the time-varying shocks that affect all firms. However, to ensure that our results are not attributable to unobservable time-invariant differences between the change and no-change firms, we extend the model by controlling for firm fixed effects instead of industry fixed effects.[53]

A limitation of the study is the lack of a control group because the mandatory adoption of SFAS 131 affected all U. S. firms around the same period (1998 for December year-end firms and 1999 for non-December-year-end firms). Thus, we follow the previous studies (e.g., Botosan and Stanford, 2005) and classify the treatment firms (labelled change firms) as those which disclosed a single segment before the adoption of SFAS 131 and were forced to reveal their previously hidden diversification status upon the adoption of SFAS 131. We classify the control firms (labelled no-change firms) as those that reported a single segment both before and after SFAS 131.[54] This comparison is relevant to our research question, because the change firms were pooled with the no-change firms before the adoption of SFAS 131 by virtue of their decision to withhold segment information (Botosan and Stanford, 2005).

[53] It is expected that our results to be spurious if our model omits any time-varying industry or state characteristics. This concern is formally addressed in section 3.5.3.3.

[54] Although all firms should adopt the changes in segment reporting enacted under SFAS 131, the control group (single segment firms) presumably already reported their segments in a manner aligned with internal organisational structures, as they have only a single segment. Thus, they did not need to change their segment definitions upon the adoption of SFAS 131.

To formally test our main hypothesis, "H1", we estimate the following difference-in-differences (DiD) specification:

$$AP/TA_{it} = \beta_0 + \beta_1 Change\ Firm_{it} + \beta_2 Post\ SFAS\ 131_{it} + \beta_3 Change\ Firm \times Post\ SFAS\ 131_{it} + \theta X_{it} + \varepsilon_{it} \quad \text{Eq. 3.1}$$

Where, AP/TA_{it} represents the use of trade credit, defined as the ratio of accounts payable to total assets.[55] Change Firm is a dummy variable that equals one for firms reported as single-segment firms under SFAS 14 but revealed previously hidden information about their industry operations (diversification status) under the adoption of SFAS 131, and zero otherwise.[56] Post SFAS 131 is a dummy variable that equals one on or after the adoption of SFAS 131, and zero otherwise. We use a window of four years before and after firms' adoption of SFAS 131.[57]

In addition, the regression includes a set of control variables, used by prior studies on trade credit (e.g., Petersen and Rajan, 1997; Choi and Kim, 2005; Love et al., 2007; Garcia-Appendini and Montoriol-Garriga, 2013), including firm size, tangibility, sales growth, R&D, leverage, cash holding, market to book ratio, return on assets, market share, and cost of goods sold.[58] We also use the firm's number of reported segments to control for the effect of segment diversity (Berger and Hann, 2007; Cho, 2015). We cluster standard errors at the firm level to control for within-firm serial dependence (Petersen, 2009).[59]

The main coefficient of interest in Equation 3.1 is β_3 that represents the difference in the effect of the adoption of SFAS 131 on the use of trade credit for change firms versus no-change firms. A statistically significant and negative coefficient on

[55] See Section 2.3.2.2 for more details concerning measures of trade credit.
[56] Note that when we control for firm fixed effect, Change Firm is absorbed by firm fixed effects and dropped from the regression.
[57] Prior studies use different estimation windows (e.g., five or three years). As a robustness check, we use alternative estimation windows. This concern is formally addressed in section 3.5.3.4.
[58] See Section 2.3.2.4 for more details regarding the effect of these control variables on trade credit.
[59] Cho (2015) and Jayaraman and Wu (2019) cluster standard errors at the industry level because these are more conservative than firm-level clustering, and especially because SFAS 131 affected several firms in the industry. As a robustness check, we use alternative clustering at the industry level and two-way clustering by firm and year or by industry and year (see Table 3.A4 in the Appendix).

Change Firm×Post SFAS 131 would provide support for our main hypothesis "H1".[60, 61]

3.5 Empirical Analysis

3.5.1 Descriptive Statistics

Panel A of Table 3.1 presents descriptive statistics for the variables used in our study over the period 1994-2002, which covers four years before and after the adoption of SFAS 131. In our sample, about 20% of the firms reported as single-segment firms under SFAS 14 and multi segments (i.e., diversification status) upon adoption of SFAS 131.[62] Further, the mean (median) use of trade credit by the sample firms accounts for 9.4% (7%) of their total assets, that is, 9.4 (7) dollars of accounts payable for every 100 dollars in total assets. In terms of other firm-specific characteristics, the mean (median) firm size, "log sales" is 4.753 (4.756) (corresponding to approximately $115 ($116) millions of sales), with a standard deviation of 1.842. Firm size is -0.074 at the 1st percentile and 9.439 at the 99th percentile, which indicates that our sample represents both small and large firms.[63] Further, the mean (median) tangible assets represent 27.5% (20.3%) of the firms' total assets. The ratio of tangible assets is 1.57% at the 1st percentile and 90.2% at the 99th percentile.

In addition, Panel A of Table 3.1 shows that the mean (median) cost of goods sold to total assets is 86.4% (69.6%). The ratio of cost of goods sold is 0.032 at the 1st percentile and 3.846 at the 99th percentile. Moreover, the average level of positive sales growth is 32.3%, while the level average of negative sales growth is -4%. About 25% of our sample firms have negative sales growth. Generally, sales growth ranges from -0.584 at the 1st percentile to 4.849 at the 99th percentile. Moreover, research and development (R&D) accounts, on average, for 6.8% of the firms' total

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[60] Note that, for our setting to work, assignment to change versus no-change firms must be exogenous. Despite the mandatory nature of SFAS 131, the no-change group is likely to include firms that should have changed their segment definitions under SFAS 131, but strategically decided to remain as no-change firms. This concern is formally addressed in section 3.5.3.1.

[61] The regression models we use to test H2, H3, H4, and H5 are similar to Equation 3.1, except that we further include interaction terms (a triple interaction term) to capture the cross-sectional differences in the effects of SFAS 131. We discuss the regression models for H2, H3, H4, and H5 in corresponding sections.

[62] This figure is similar to prior studies that use the same type of change and no-change firms in their samples (e.g., Botosan and Stanford, 2005; Benz and Hong, 2019).

[63] Sales are expressed in 2000 dollars.

assets. About 50% of our sample firms do not invest in R&D. In addition, on average, firms have a negative return on assets, "ROA", and the mean of ROA is -3.8%, while the median of ROA is positive (3.4%). About 25% of our sample firms have negative ROA. Further, the mean (median) of the market to book ratio, "MTB", is 2.360 (1.575). The MTB ranges from 0.583 at the 1st percentile to 12.33 at the 99th percentile.

Moreover, Panel A of Table 3.1 shows that cash holding represents 20.2% of the firm's total assets, ranging from 0% at the 1st percentile to 89.3% at the 99th percentile. The mean of the leverage ratio is 20%, and the ratio ranges from 0% at the 1st percentile to 91.6% at the 99th percentile. Further, the average market share is 0.2%, ranging from 0% at the 1st percentile to 4.1% at the 99th percentile. Finally, the average number of segments during the full sample period is 1.131, which ranges from one segment at the 1st percentile to three segments at the 99th percentile.

Finally, Panel B of Table 3.1 presents the Pearson correlation coefficients of the main variables. The table shows that the ratio of accounts payable to total assets (AP/TA) is significantly positively correlated with Firm Size, Cost of Goods Sold, Negative Growth, and Leverage, and is significantly negatively correlated with Positive Growth, R&D, ROA, MTB, and Cash Holding. In addition, AP/TA is significantly negatively correlated with Post SFAS 131, suggesting a decline in the use of trade credit in the post-SFAS 131 period. In addition, AP/TA is insignificantly negatively correlated with Change Firm.[64]

Thus far, we have provided a description of the firm-specific characteristics in our sample. In the next subsection, we discuss our main results regarding the impact of exogenous changes in the information environment associated with the mandatory segment information disclosure on the firm's use of trade credit

[Insert Table 3.1 here]

3.5.2 Main Results

Having discussed the descriptive statistics of our entire sample, we now consider the main results for the effect of the mandatory segment information disclosure,

[64] Variance-Inflation-Factor (VIF) analyses for each independent variable used in the study show that the highest VIF is 9.02, which is below 10; the threshold beyond which multicollinearity may be a problem (Hair et al., 2009). This suggests that our models are not prone to serious multicollinearity problems. See Table 3.A2 in the Appendix for VIF analyses.

SFAS 131, on the use of trade credit. We start with a univariate Difference-in-Differences (DiD) analysis in a sample of change firms and no-change firms during the pre- and post-SFAS 131 periods in Section 3.5.2.1. We then perform the DiD tests in a multivariate regression framework in Section 3.5.2.2. In Section 3.5.2.3, we test the timing of changes in the use of trade credit surrounding the adoption of SFAS 131, while in section 3.5.2.4, we conduct placebo tests to strengthen our inference about the effect of the adoption of SFAS 131 on trade credit.

3.5.2.1 Univariate Difference-in-Differences (DiD) Analysis

Table 3.2 presents univariate Difference-in-Differences (DiD) results that compare change and no-change firms in the pre- and post- SFAS 131 periods. In the pre-SFAS 131 period, the mean of accounts payable to total assets is 9.8% for change firms (in Column 1) and 9.7% for no-change firms (in Column 2). This suggests that change firms, on average, used slightly more trade credit relative to no-change firms in the pre-SFAS 131 period. However, the mean difference in accounts payable to total assets between the change and no-change firms in the pre-SFAS 131 period is 0.01 percentage point (in Column 3), which is statistically insignificant (t-statistic=0.18). This indicates that there is no statistical significant difference in the use of trade credit between change and no-change firms before the adoption of SFAS 131.

Moreover, in the post-SFAS 131 period, the mean of accounts payable to total assets is 8.8% for change firms (in Column 4) and 9.3% for no-change firms (in Column 5). This suggests that change firms, on average, use less trade credit relative to no-change firms in the post-SFAS 131 period. Nevertheless, the mean difference in accounts payable to total assets between the change and no-change firms in the post-SFAS 131 period is statistically insignificant (t-statistic=-1.30).

Furthermore, the change in accounts payable to total assets between the pre- and post-SFAS 131 periods for change firms is -1 percentage point (i.e., 8.8% - 9.8%) (Columns 4 and 1), which is negative and statistically significant (t-statistic=-3.80, untabulated). The change in accounts payable to total assets between the pre- and post-SFAS 131 periods for no-change firms is -0.04 percentage points (i.e., 9.3% - 9.7%) (Columns 5 and 2), which is negative and statistically significant (t-statistic=-2.90, untabulated). Despite the change in accounts payable to total assets between the pre- and post-SFAS 131 periods for no-change firms being significant, the difference in accounts payable to total assets between the pre- and post-SFAS 131 period for change firms is greater than the difference for no-change firms.

Moving to the univariate difference-in-differences results reported in Column (7) of Table 3.2, we find that the mean effect of SFAS 131 on accounts payable to total assets is -0.06 percentage points for change firms (relative to no-change firms) and that it is statistically significant at the 5% level (t-statistic=-2.06). These results are consistent with our main hypothesis, “H1”, that change firms experience a greater reduction in the use of trade credit in the post-SFAS 131 period relative to the pre-SFAS 131 period than no-change firms.

Regarding the univariate difference-in-differences for our control variables, Column (7) of Table 3.2 shows that the Firm Size, Tangibility, Negative Growth, ROA, Cash Holding, and Market Share exhibit insignificant difference-in-differences results. On the other hand, Cost of Goods Sold, Positive Growth, R&D, MTB, Leverage and Number of Segments exhibit significant difference-in-differences results in Column (7).

Thus far, the evidence from the univariate Difference-in-Differences (DiD) tests suggests that the change firms decrease their use of trade credit after the adoption of SFAS 131 more than no-change firms. To provide more definitive evidence, in the next stage, we conduct regression analysis.

[Insert Table 3.2 here]

3.5.2.2 Multivariate Difference-in-Differences (DiD) Analysis

We now move on with the formal regression analysis of the impact of the exogenous shock on the firm's information environment, caused by the adoption of SFAS 131, on the use of trade credit “H1”. Table 3.3 presents the estimates of the difference-in-differences specification described in Equation 3.1. We estimate different regressions with industry (based on Fama–French 48 industry classifications) and year fixed effects in Columns (1) and (2), and with firm and year fixed effects in Columns (3) and (4). We estimate the Difference-in-Differences (DiD) model without covariates in Columns (1) and (3) and with covariates in Columns (2) and (4). In all regressions, the standard errors are clustered at the firm level. Table 3.3 shows that the use of trade credit decreases after the adoption of SFAS 131 for firms that disclose a single segment prior to the adoption of SFAS 131 but are forced to reveal their previously hidden diversification status upon the adoption of SFAS 131. Across all Columns (1)-(4), the coefficient on Change Firm×Post SFAS 131 is negative and statistically significant. The coefficients on Change Firm×Post SFAS 131 range from -0.0178 to -0.0061. More specifically, in Column (1), the coefficient on Change Firm×Post SFAS 131 is -0.0069 and is statistically significant at the 1% level (t-statistic=-2.61). In Column (2), it is -0.0125 and is statistically significant at the 5% level (t-statistic=-1.99). In Column (3), the coefficient on Change Firm×Post SFAS 131 is -0.0061 and is statistically significant at the 1% level (t-statistic=-2.67). In Column (4), the coefficient is -0.0178 and is statistically significant at the 1% level (t-statistic=-2.91).

In terms of the economic significance, in the results for Column (4), the 0.0178 decrease in the use of trade credit for change firms (Column 4) translates into approximately a 19% (25%) decrease relative to the mean (median) sample accounts payable to total assets (i.e., −0.0178 divided by 0.094 (0.07)). To put all specifications, Columns (1)-(4), in perspective, the decrease in the use of trade credit for change firms translates into approximately a 6.5% to 19% (8.7% to 25%) decrease relative to the mean (median) sample accounts payable to total assets.

With respect to the control variables, Table 3.3 indicates that the signs of the estimated coefficients for the control variables are relatively consistent with existing empirical literature (e.g., Petersen and Rajan, 1997; Klapper et al., 2012; Garcia-Appendini and Montriol-Garriga, 2013). In the specification with firm and year fixed effects (Column 4), the coefficients on Firm Size, Tangibility, ROA, and Cash Holding are significantly negative. On the other hand, the coefficients on Cost of Goods Sold, Negative Growth, R&D, and MTB are significantly positive. The coefficients on Positive Growth and Market Share are not statistically significant. Moreover, the coefficient on Leverage is statistically significant in the specification with industry fixed effects (Column 2), but becomes insignificant after controlling for firm fixed effects (Column 4).[65]

Overall, our DiD results in Table 3.3 are consistent with our first hypothesis, “H1”, that firms that disclose a single segment prior to the adoption of SFAS 131 but are

[65] Although our univariate analysis shows that the use of trade credit significantly decreases for change and no-change firms in the post SFAS 131 period, multivariate analysis shows that the use of trade credit significantly increases in the post-SFAS 131 period. In particular, in Column 3 of Table 3.3, the coefficient on Post SFAS 131 is positive and significant (t-statistic=3.27). However, this impact only appears when using firm fixed effects without covariates. When we use firm fixed effects and covariates, this impact is insignificant.

forced to reveal their previously hidden diversification status upon the adoption of SFAS 131 experience a drop in the use of trade credit in the post-SFAS 131 period relative to the pre-SFAS 131 period than the no-change firms (i.e., firms that disclose a single segment in the pre- and post- SFAS 131 periods). To validate our DiD estimates, in the next subsection, we explore the timing of the changes in the use of trade credit surrounding the adoption of SFAS 131 to examine the parallel trend assumption and the persistence of the treatment effect.

[Insert Table 3.3 here]

3.5.2.3 Timing of Changes in the Use of Trade Credit Surrounding the Adoption of SFAS 131

We now explore the timing of the changes in the use of trade credit surrounding the adoption of SFAS 131 to test the parallel trend assumption underlying our Difference-in-Differences estimation, and to also examine the persistence of trade credit declines. The parallel trend assumption states that, in the absence of treatment, the difference in outcomes between the treatment and control groups is time-invariant (Roberts and Whited, 2013). In our setting, the parallel trend assumption requires similar trends in the use of trade credit during the pre-SFAS 131 period for both change firms and no-change firms. To test whether change and no-change firms exhibit any differential changes in the use of trade credit before the adoption of SFAS 131, we follow Kraft et al. (2018) and examine the pre-treatment time period indicator variables.[66] We do this by extending Equation 3.1 with the dummy variable Before(-1) (Before(-2)) interacted with the Change Firm dummy, where Before(-1) (Before(-2)) is equal to one for the one-year (two-year) period before the adoption of SFAS 131, and zero otherwise.

Panel A of Table 3.4 reports the results. Column (1) of Panel A shows that the coefficient on the Change Firm×Before(-1) is statistically and economically insignificant. This suggests that changes in the use of trade credit for change and no-change firms are not statistically different one year prior to the adoption of SFAS 131. The coefficient on the main variable of interest, Change Firm×SFAS 131, continues to be negative and with comparable magnitude to those shown in Column

[66] Testing the parallel trends assumption by using pre-treatment time period indicator variables is recommended by many studies (e.g., Angrist and Pischke, 2009; Lechner, 2011).

(4) of Table 3.3. Similarly, in Column (2) of Panel A, the coefficient on the Change Firm×before(-2) is statistically insignificant, and the coefficient on the main variable of interest, Change Firm×Post SFAS 131, continues to be negative and statistically significant. Overall, our parallel trends test suggests that change and no-change firms follow parallel trends in the use of trade credit for the two years prior to the adoption of SFAS 131, and, as discussed below, these trends diverge only after the adoption of SFAS 131.

Next, we turn to the evidence on the persistence of the decline of trade credit usage for the change firms. If the decline in the use of trade credit reflects a shift to a new equilibrium, with lower levels of trade credit following the change in the segment disclosure regime, then a decline in the use of trade credit should not be temporary and should persist over time. To assess the persistence, we also follow Kraft et al.(2018) and adjust Equation 3.1 by replacing Post SFAS 131 with two dummy variables that interact with the Change Firm dummy: After(+1,+2) and After(+3,+4). After(+1,+2) is a dummy variable that equals one for the first two years subsequent to the adoption of SFAS 131, and zero otherwise; After(+3,+4) is a dummy variable that equals one for year three and after the adoption of SFAS 131, and zero otherwise. Estimates of the modified specification are presented in Column (3) of Panel A. The coefficients on both Change Firm×After(+1,+2) and Change Firm×After(+3,+4) are negative and statistically significant at the 1% level (t-statistics=-2.65 and -3.05 respectively). Overall, these findings suggest that the decline in the use of trade credit after the adoption of SFAS 131 is not short-lived, but persists over time.

In addition to examining the parallel trend assumption and the persistence of the decline of trade credit usage in Panel A of Table 3.4, we further examine the dynamics of the use of trade credit surrounding the adoption of SFAS 131. This test also verifies the parallel trend assumption for our DiD estimation and also examines the timing of changes in the use of trade credit relative to the timing of the adoption of SFAS 131 by using a dynamic DiD regression. If reverse causality drives our results, we should observe a decrease in the use of trade credit of change firms relative to no-change firms prior to the adoption of SFAS 131. Such evidence would cast doubt on the validity of our DiD estimation, as it implies a violation of the parallel trends assumption.

In Panel B of Table 3.4, we estimate a dynamic DiD regression where we extend our DiD model in Table 3.3 by replacing the Post SFAS 131 indicator with year-specific indicators. In particular, we re-estimate Equation 3.1 by replacing the Post SFAS 131 indicator with T+i (where i equals -3, -2, -1, +1, +2, +3 and +4). The values of T-i are equal to one if the observation occurs i years before (after) the adoption of SFAS 131 for negative (positive) values of i) and zero otherwise. We then interact these indicator variables with the Change Firm indicator in dynamic DiD regressions. Our main variables of interest are the interaction terms.

We find that the coefficients on Change Firm×T-3, Change Firm×T-2, and Change Firm×T-1 are close to zero and statistically insignificant, suggesting that change firms do not decrease their use of trade credit relative to no-change firms before the adoption of SFAS 131. In contrast, the coefficients on Change Firm×T+1, Change Firm×T+2, Change Firm×T+3, and Change Firm×T+4 are negative and significant, indicating that change firms start to decrease their use of trade credit relative to no-change firms after the adoption of SFAS 131. Overall, these results suggest that change firms decrease their use of trade credit relative to that of no-change firms only after the adoption of SFAS 131, but not before. Thus, reverse causality or a violation of the parallel trends assumption does not explain our main result that the adoption of SFAS 131 leads to a decrease in the use of trade credit.

[Insert Table 3.4 here]

We also graphically investigate the dynamic impact of the adoption of SFAS 131 on the use of trade credit and present the evidence in Figure 3.1. We use the same specification used in Panel B of Table 3.4, using a series of dummy variables corresponding to pre-treatment lags (up to 3 years) and post-treatment leads (up to 4 years) to track the year-by-year impacts of SFAS 131 on the use of trade credit. In Figure 3.1, we plot the estimated coefficients and the 95% confidence intervals, adjusted for firm-level clustering. The coefficients on the interactions between the Change Firm dummy and time indicators dummy variables are insignificantly different from zero for all years before the adoption of SFAS 131, with no trends in the use of trade credit prior to the adoption of SFAS 131. Notably, the figure shows that the use of trade credit decreases from the year prior to SFAS 131 adoption (t-1) to the adoption year (t+1). The differences in the use of trade credit between change firms and no-change firms are negative and statistically significant (at the 5% level) starting from the first year of SFAS 131 adoption (t+1). This suggests that the adoption of SFAS 131 have a significant impact on the use of trade credit. Collectively, Figure 3.1 lends further confidence to the validity of our empirical strategy.

[Insert Figure 3.1 here]

3.5.2.4 Placebo Tests

There is a potential concern that the reduction in the use of trade credit after the adoption of SFAS 131 is the result of an increased information disaggregation at the segment level (i.e., changes in the firm's information environment at the segment level) rather than revealing the firm's diversification status. Previous research (e.g., Berger and Hann, 2003; Herrmann and Thomas, 2000; Street et al., 2000) shows that the adoption of SFAS 131 induces firms to provide more disaggregated segment-reporting, which has a positive impact on the precision of market participants' beliefs. If this is the case, then we should observe that more disaggregated information at the segment level, rather than the revelation of the firm's diversification activities, would lead to a decrease in the use of trade credit after the adoption of SFAS 131.

To address this concern, we use a placebo test to examine whether more disaggregated information at the segment level, instead of revealed diversification status, explains the change in the use of trade credit after the adoption of SFAS 131. We construct a pseudo-treatment group including firms that disclosed more operating segments under SFAS 131 but operated in the same four-digit SIC code industry during our sample period (i.e., non-diversified placebo firms).[67] More specifically, these placebo change firms were single segment and single-industry firms before SFAS 131 and became multi-segment and single-industry firms after the adoption of SFAS 131. In contrast, our change firms, used in our baseline analysis, were single segments and single-industry firms before SFAS 131 and became multi-segment and diversified firms after the adoption of SFAS 131. A good example of cases in which firms that disclosed more operating segments under SFAS 131 but operated in the same four-digit SIC code industry has been highlighted by Benz and Hoang (2020). They show that Oshkosh operated in SIC 3711 during their sample period and disclosed a single segment called "specialized motor vehicles"

[67] We borrow the idea of this placebo test from Benz and Hoang (2020).

before the adoption of SFAS 131 and three segments (namely, "commercial trucks", "fire and emergency trucks", and "defence tactical trucks") after the adoption of SFAS 131. Notably, these three segments are in the same SIC code industry, namely, SIC 3711, meaning that this is not a diversified, despite multi-segment, firm after the adoption of SFAS 131.

Table 3.5 presents the results for the placebo test. We replace the indictor variable, Change Firms, in Equation 3.1 with an indicator variable, Placebo, that equals to one for firms in the pseudo-treatment group described above, and zero for no-change firms. If information disaggregation at the segment level could explain the change in the use of trade credit, then the coefficient on Placebo×Post SFAS 131 would be negative and significant. In other words, we should observe a decrease in the use of trade credit for placebo change firms after the adoption of SFAS 131 relative to no-change firms. In both Columns (1) and (2) (with and without control variables respectively), the coefficient on Placebo×Post SFAS 131 is insignificantly different from zero. Although the coefficients on Placebo×Post SFAS 131 are negative, they are much smaller in magnitude than those reported in Table 3.3. The corresponding t-statistics are smaller and statistically insignificant, indicating no significant reduction in the use of trade credit for placebo change firms relative to no-change firms. This finding helps rule out the alternative explanation that the reduction in trade credit after the adoption of SFAS 131 is driven by an increased information disaggregation at the segment level.

[Insert Table 3.5 here]

3.5.3 Robustness Tests

In this subsection, we conduct some additional tests to assess the sensitivity of our findings. Specifically, we examine whether our results are robust to an alternative control group, a matched sample, the inclusion of additional fixed effects, alternative estimation windows, and alternative measures of trade credit.

3.5.3.1 Alternative Control Group

A key assumption of our DiD analysis is that the assignment to change versus no-change firms is exogenous. Although the adoption of SFAS 131 forces mandatory change in segment disclosure, the no-change group is likely to contain firms that must have changed their segment definitions under SFAS 131, but strategically decided to remain as no-change firms. Consequently, the change versus no-change classification may not be exogenous (Cho, 2015). To limit this possibility, we replace our control group with a different type of firms, multi-segment firms that disclose the same number of segments before and after SFAS 131.[68] Our sample includes 1,509 firm-year observations of such firms.

Panel A of Table 3.6 reports the results. In Column (1) of Panel A, the no-change firms are multi-segment firms that disclose the same number of segments before and after SFAS 131. In Column (2) of Panel A, we use both multi-segment firms and single-segment firms as our control group. In both Columns (1) and (2), the coefficient on Change Firm×Post SFAS 131 is negative and statistically significant at 5% (t-statistics=-2.11 and -2.02 respectively). Overall, our results are robust to alternative control groups.

3.5.3.2 Matched Difference-in-Differences (DiD) Regression

Our results so far suggest a negative and significant impact of the adoption of SFAS 131 on the use of trade credit and that change firms and no-change firms follow parallel trends before the adoption of SFAS 131. However, our results could lead to biased inferences if the reduction in the use of trade credit after the adoption of SFAS 131 is unrelated to the changes in the firm's information environment caused by the change in segment reporting quality. For example, if the firms that reveal new information about their segments after the adoption of SFAS 131 are fundamentally different from single segment firms, then unobservable firm characteristics could drive our results. Such differential trends might result from the fact that firm characteristics are unbalanced across change firms and no-change firms if firms systematically self-select into the change firms group. As noted by Botosan and Stanford (2005), single segment firms tend to be substantially smaller than firms that reveal new information about their corporate diversification status (i.e., single to multi-segment firms). To address the differences between change firms and no-change firms, we undertake a propensity score-matched (PSM) sample based on ex-ante firm characteristics to correct for any possible differential trends (Rosenbaum and Rubin, 1983; Dehejia and Wahba, 2002).

[68] We use the same control group as in Cho (2015).

To estimate the propensity scores, we first run a logistic regression that estimates the probability of being a change firm using a range of firm characteristics (i.e., firm size, tangibility, market-to-book ratio, leverage, R&D, ROA, cash holding, sales growth, market share and Fama-French 48 industry dummies) during the year before the adoption of SFAS 131. We then match each change firm with a no-change firm, based on different matching procedures: a one-to-one propensity score matching with replacement and without replacement respectively. We require the propensity score distance between each matched pair to be within a caliper of 0.01. Then, we re-run our main DiD test on the propensity score matched samples. Panel B of Table 3.6 presents the results for the matched DiD regression. In Column (1), change firms are matched with no-change firms based on one-to-one propensity score matching with replacement. In Column (2), the matched sample is based on one-to-one propensity score matching without replacement. In both columns, the coefficients on Change Firm×Post SFAS 131 are negative and significant at the 1% level (t-statistics=-3.26 and -.2.91 respectively) and similar in magnitude (-0.0221 and -0.025, respectively) relative to the results reported in Table 3.3 (i.e., -0.0178). Overall, these results suggest that the observed negative impact of SFAS 131 on the use of trade credit is not driven by differences in firm characteristics.

3.5.3.3 Additional Fixed Effects

In our baseline DiD regression based on Equation 3.1, we include industry fixed effects to remove time-invariant industry-specific characteristics, year fixed effects to control for common time trends, and firm fixed effects to control for unobservable time-invariant differences between the change and no-change firms. However, the negative impact of SFAS 131 on the use of trade credit is still likely to be spurious if our model omits some time-varying industry characteristics. To address this concern, we include industry-by-year fixed effects (i.e., two-dimensional fixed effects) in our DiD model. This ensures that our model captures change and no-change firms in the same industry, which mitigates unobserved time-varying industry shocks to post-treatment trends in the use of trade credit. Moreover, the negative impact of SFAS 131 on the use of trade credit is likely to be driven by some time-varying state characteristics (e.g., state-level regulations, local economic conditions). Thus, we further control for state-by-year fixed effects in our DiD model.

Panel C of Table 3.6 presents the results, controlling for additional fixed effects. In Column (1), we include industry year fixed effects in addition to firm fixed effects. In Column (2), in addition to industry-year fixed effects, we include state-year fixed effects. The results are qualitatively similar to the baseline evidence in Table 3.3. The coefficient on Change Firm×Post SFAS 131 is -0.0169 and significant at the 1% level (t-statistic=-2.60) when we control for industry-year fixed effects, while it is -0.0172 and significant at the 5% level (t-statistic=-2.56) when we control for both industry-year and state-year fixed effects. Overall, our results are robust to the inclusion of additional fixed effects that control for unobservable time-variant industry-specific and state-specific heterogeneity.

3.5.3.4 Different Estimation Windows

Prior studies (e.g., Cho, 2015; Benz and Hoang, 2019; Jayaraman and Wu, 2019; Altieri, 2020), which exploit the adoption of SFAS 131 as an experimental setting, use different sample periods (i.e., a window of 2-5 years before and after SFAS 131). The rationale behind using different sample periods is that the choice of the window of years before and after SFAS 131 is restricted to the research design and data availability. For example, Cho (2015) uses a window of two years before and after the adoption of SFAS 131 because his research question is based on restated segment data available for just one or two years preceding the adoption of SFAS 131. However, Jayaraman and Wu (2019) undertake a window of five years before and after SFAS 131 to examine the impact of this regulatory change on investment sensitivity.[69]

Panel D of Table 3.6 presents the results. In Column (1) of Panel D, we use a window of five years before and after the adoption of SFAS 131. Our inferences remain unchanged: the coefficient on Change Firm×Post SFAS 131 remains negative and significant at the 1% level (t-statistic=-2.73). Moreover, In Column (2) of Panel D, we use a window of three years before and after the adoption of SFAS 131. Again, the results remain unchanged and significant at the 5% level (t-statistic=-2.44). Collectively, the results reported in Panel D indicate that using alternative estimation windows does not qualitatively alter our results.

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[69] Moreover, prior research (e.g., Bertrand et al., 2004) argues that long event periods are likely to generate upward biased inference levels in shock-based tests. Thus, we use shorter event periods to mitigate this concern.

3.5.3.5 Alternative Measures of Trade Credit

In our final sensitivity test, we use two alternative measures of trade credit as a robustness check. The first measure is the ratio of accounts payable to costs of goods sold. The second measure is the ratio of accounts payable to total sales. Column (1) of Table 3.6, Panel E shows that our inferences remain unchanged: the coefficient on Change Firm×Post SFAS 131 remains negative and significant at the 1% level (t-statistic=-2.83). Column (2) of Table 3.6, Panel E shows that again our inferences remain unchanged: the coefficient on Change Firm×Post SFAS 131 remains negative and significant at the 5% level (t-statistic=-2.45). Overall, these findings confirm that our results are robust to alternative measures of trade credit.

[Insert Table 3.6 here]

3.5.4 Cross-Sectional Analysis

Having established that SFAS 131 affects trade credit negatively through the change in the firm's information environment that induces firms to substitute trade credit for less expensive sources of financing, in this section, we provide additional evidence of this relationship in the cross-section. To better understand this relationship, we explore settings in which the impact of SFAS 131 adoption on the use of trade credit is likely to vary. In particular, we examine whether the impact of SFAS 131 on the use of trade credit varies with: (1) ex-ante default risk, (2) information opacity, (3) corporate governance mechanisms, and (4) auditing quality. To conduct the analyses, we rerun regressions based on Equation 3.1 and further include interaction terms to capture the cross-sectional differences in the effects of SFAS 131.

3.5.4.1 Default Risk

Our first cross-sectional test examines whether the impact of the adoption of SFAS 131 on the use of trade credit varies with the default risk facing change firms during the pre-SFAS 131 period. The second hypothesis, "H2", implies that the effect of SFAS 131 on the use of trade credit is greater for change firms that suffered more severe default risk during the pre-SFAS 131 period. To test this prediction, we use two measures of default risk, the Ohlson (1980) O score and the Altman (1968) Z score. For the O score, we construct an indicator variable, Ohlson, which takes a value of one if the firm's Ohlson probability of bankruptcy is greater than 50% during the pre-SFAS 131 period (one year before the adoption of SFAS 131), and zero otherwise. For the Z score, we construct an indicator variable, Altman, which takes a value of one if the firm's Altman Z score of bankruptcy is below 1.81 during the pre-SFAS 131 period (one year before the adoption of SFAS 131), and zero otherwise. We then add the interaction terms of Change Firm×Post SFAS 131×Ohlson (Altman) and Ohlson (Altman)×Post SFAS 131 to Equation 3.1, allowing us to test the triple interaction effect.[70] In this test, the coefficient on Change Firm×Post SFAS 131 captures the incremental change in use of trade credit for change firms with low ex-ante default risk, and the coefficient on Change Firm×Post SFAS 131×Ohlson (Altman) captures the incremental change in the use of trade credit for change firms with high ex-ante default risk relative to those with low default risk. The variable of interest is Change Firm×Post SFAS 131×Ohlson (Altman). According to our second hypothesis, we expect the coefficient on Change Firm×Post SFAS 131×Ohlson (Altman) to be negative.

Table 3.7 shows the results for the cross-sectional test based on ex-ante default risk. In Column (1), the ex-ante default risk is measured using the O score. The table shows that the coefficient on Change Firm×Post SFAS 131×Ohlson is negative and significant at the 5% level. Specifically, the coefficient on Change Firm×Post SFAS 131 is -0.0172 (t-statistic=-2.76), and the coefficient on Change Firm×Post SFAS 131×Ohlson is -0.0125 (t-statistic=-2.26). For change firms with high ex-ante default risk (i.e., high Ohlson probability of bankruptcy), their use of trade credit decreases by 2.97 (=1.25 + 1.72) percentage points, while the use of trade credit decreases by 1.72 percentage points for change firms with low ex-ante default risk.

In Column (2) of Table 3.7, the ex-ante default risk is measured using the Z score. Again, we find the coefficient on Change Firm×Post SFAS 131×Altman is significantly negative at the 10% level. The coefficient on Change Firm×Post SFAS 131 is -0.0164 (t-statistics=-2.65), and the coefficient on Change Firm×Post SFAS 131×Altman is -0.0101 (t-statistics=-1.69). For change firms with high ex-ante

[70] Note that Change Firm, Ohlson (Altman), and Change Firm×Ohlson (Altman) are dropped from the regression because they are subsumed by firm fixed effects. Also, in the subsequent cross-sectional analyses, Change Firm, the cross-sectional variable, and Change Firm interacted with the cross-sectional variable are dropped from the regression for the same reason (firm fixed effects).

default risk (i.e., high Altman probability of bankruptcy), their use of trade credit decreases by 2.65 (=1.01 + 1.64) percentage points, while the use of trade credit decreases by 1.64 percentage points for change firms with low ex-ante default risk. Together, these results are consistent with "H2", suggesting that the reduction in the use of trade credit is more pronounced among change firms with higher default risk during the pre-SFAS 131 period.

Overall, the results support the view that the adoption of SFAS 131 enables firms with high ex-ante default risk to move away from trade credit to other sources of financing. These firms may resort to their suppliers more during the pre-SFAS 131 period because their suppliers have an information advantage over financial institutions in eliciting information about their customers' default risk more quickly than financial institutions. However, the adoption of SFAS 131 leads to a revision in capital market participants' beliefs about a firm's diversification activities, enhancing the market participants' assessments of the firm's default risk. Specifically, the adoption of SFAS 131 reduces the information asymmetry with respect to the firm's true underlying diversification and the resulting co-insurance effect that can lower the perceived default risk (Lewellen, 1971), which is why we find that the change firms with higher pre-SFAS 131 default risk benefit more from the adoption of SFAS 131.

[Insert Table 3.7 here]

3.5.4.2 Information Environment

Our second cross-sectional test examines whether the impact of the adoption of SFAS 131 on the use of trade credit varies with the level of the firm's information opacity. The third hypothesis, "H3", implies that the effect of SFAS 131 on the use of trade credit is greater for change firms with a more opaque information environment during the pre-SFAS 131 period. To test this hypothesis, we use two proxies for information opacity. The first proxy is the probability of informed trading (PIN), which captures the ratio of trading by informed investors to total trading in the stock. This variable is commonly used as a measure of information asymmetry or opacity, as it measures information risk that is systematically priced by investors (Easley and O'Hara, 2004). The second proxy is a firm idiosyncratic risk (IR), defined as the standard deviation of the residual return from the Fama-French three-factor model (Ang et al., 2006). This variable has been used by prior research as a proxy for information asymmetry or opacity (e.g., Bhagat et al., 1985; Blackwell et al., 1990). When PIN or IR is higher, firms are more informationally opaque.

We construct an indicator variable, High PIN (High IR), which takes a value of one for firms in the top quartile of the sample distribution of PIN (IR) during the pre-SFAS 131 period (one year before the adoption of SFAS 131) and zero otherwise. Similar to the cross-sectional tests discussed above, we add the interaction terms of Change Firm×Post SFAS 131×High PIN (High IR) and High PIN (High IR)×Post SFAS 131 to Equation 3.1, allowing us to test the triple interaction effect. In this test, the coefficient on Change Firm×Post SFAS 131 captures the incremental change in use of trade credit for change firms with lower information opacity, and the coefficient on Change Firm×Post SFAS 131×High PIN (High IR) captures the incremental change in the use of trade credit for change firms with higher information opacity relative to those with lower information opacity. The variable of interest is Change Firm×Post SFAS 131×High PIN (High IR). According to "H3", we expect the coefficient on Change Firm×Post SFAS 131×High PIN (High IR) to be negative.

Table 3.8 reports the results for the cross-sectional test based on information opacity. In Column (1), information opacity is proxied by PIN. The table shows that the coefficient on Change Firm×Post SFAS 131×High PIN is negative and significant at the 1% level. The results show that the coefficient on Change Firm×Post SFAS 131 is -0.0144 (t-statistic=-2.29), and the coefficient on Change Firm×Post SFAS 131×High PIN is -0.0134 (t-statistic=-2.78). For change firms with a more opaque information environment (high PIN) during the pre-SFAS 131 period, their use of trade credit decreases by 2.78 (=1.34+ 1.44) percentage points, while the use of trade credit decreases by 1.44 percentage points for change firms with a less opaque information environment during the pre-SFAS 131 period.

Column (2) of Table 3.8 presents the results when information opacity is proxied by idiosyncratic risk. Again, similar to the results above, we find the coefficient on Change Firm×Post SFAS 131×High IR is significantly negative at the 10% level. In particular, the coefficient on Change Firm×Post SFAS 131 is -0.0157 (t-statistic=-2.50), and the coefficient on Change Firm×Post SFAS 131×High IR is -0.0111 (t-statistic=-1.81). This suggests that for change firms with a more opaque information environment (high idiosyncratic risk) during the pre-SFAS 131 period, their use of trade credit decreases by 2.68 (=1.11 + 1.57) percentage points, while the use of trade credit decreases by 1.57 percentage points for change firms with a less opaque information environment during the pre-SFAS 131 period. Collectively, the results in Columns (1) and (2) of Table 3.8 provide evidence consistent with "H3" that the reduction in the use of trade credit is more pronounced for change firms that are more informationally opaque during the pre-SFAS 131 period.

In summary, the results are consistent with the notion that the adoption of SFAS 131 improves the firm's information environment, which, in turn, reduces information asymmetry between firms and their capital providers and enables firms to rely less on trade credit financing. As a result, firms with limited access to sources of financing because of their high information opacity during the pre-SFAS 131 period benefit more from the adoption of SFAS 131.

[Insert Table 3.8 here]

3.5.4.3 Corporate Governance

Our third cross-sectional test examines whether the impact of the adoption of SFAS 131 on the use of trade credit varies with the quality of corporate governance mechanisms. The fourth hypothesis, "H4", implies that the effect of SFAS 131 on the use of trade credit is greater for change firms with weak governance during the pre-SFAS 131 period. To test this prediction, we follow the literature (e.g., Chung and Zhang, 2011; Cain et al., 2017) and use two indicators of weak external governance, namely, low institutional ownership and low takeover threats. To measure weak governance from institutional investors, we use two variables. The first variable is based on the percentage of shares outstanding held by institutions, and we construct an indicator variable, Low IO, which takes a value of one for firms in the bottom quartile of the institutional ownership percentage distribution during the pre-SFAS 131 period (one year before the adoption of SFAS 131) and zero otherwise. The second variable is based on the presence of blockholders, defined as shareholders who hold at least 5% of a firm's outstanding shares. For this variable, we construct an indicator variable, No Blockholders, which takes a value of one for firms without blockholder ownership during the pre-SFAS 131 period (one year before the adoption of SFAS 131) and zero otherwise. Again, similar to the cross-sectional tests above, we add the interaction terms of Change Firm×Post SFAS 131×Low IO (No Blockholders) and Low IO (Blockholders)×Post SFAS 131 to

Equation 3.1, allowing us to test the triple interaction effect. The coefficient on Change Firm×Post SFAS 131 captures the incremental change in use of trade credit for change firms with high IO, and the coefficient on Change Firm×Post SFAS 131×Low IO (No Blockholders) captures the incremental change in the use of trade credit for change firms with low IO during the pre-SFAS 131 period relative to those with high IO. The variable of interest is Change Firm×Post SFAS 131×Low IO (No Blockholders). According to "H4", we expect the coefficient on Change Firm×Post SFAS 131×Low IO (No Blockholders) to be negative.

Panel A of Table 3.9 shows the results for the cross-sectional test based on governance quality measured by institutional ownership. Using the percentage of shares outstanding held by institutions in Column (1), we find that the coefficient on Change Firm×Post SFAS 131×Low IO is negative and significant at the 10% level. More specifically, the coefficient on Change Firm×Post SFAS 131 is -0.0151 (t-statistic=-2.58), and the coefficient on Change Firm×Post SFAS 131×Low IO is -0.0082 (t-statistic=-1.83). This suggests that for change firms with a low IO during the pre-SFAS 131 period, their use of trade credit decreases by 2.33 (=0.82+ 1.51) percentage points, whereas the use of trade credit decreases by 1.51 percentage points for change firms with high IO during the pre-SFAS 131 period. The results are consistent when using blockholder ownership as a governance measure. In Column (2), we find that the coefficient on Change Firm × Post SFAS 131 × No Blockholders is negative and significant at the 10% level. In particular, the coefficient on Change Firm×Post SFAS 131 is -0.0150 (t-statistic=-2.56), and the coefficient on Change Firm×Post SFAS 131×No Blockholders is -0.0074 (t-statistic=-1.77). This means that that for change firms without blockholder ownership during the pre-SFAS 131 period, their use of trade credit decreases by 2.24 (=0.74+ 1.50) percentage points, while the use of trade credit decreases by 1.50 percentage points for change firms with blockholder ownership during the pre-SFAS 131 period. Generally, using institutional ownership to measure governance quality, our results suggest that the effect of SFAS 131 is more pronounced among change firms with weak governance during the pre-SFAS 131 period.

Moreover, prior research suggests that takeover protection represents strong managerial power. Bebchuk et al. (2009) develop an entrenchment index (E-index) based on six provisions that limit shareholder rights and make potential hostile takeovers more difficult. These provisions include staggered boards, limits to shareholder bylaw amendments, poison pills, golden parachutes, supermajority requirements for mergers, and charter amendments. A high entrenchment index (E-index) indicates weak shareholder rights, implying weak corporate governance. In Panel B of Table 3.9, we use another indicator for weak governance, High E-index, which takes a value of one for firms that are in the top quartile of the E-index during the pre-SFAS 131 period. We then add the interaction terms of Change Firm×Post SFAS 131×High E-index and High E-index×Post SFAS 131 to Equation 3.1, allowing us to test the triple interaction effect. The variable of interest is Change Firm×Post SFAS 131×High E-Index. Panel B of Table 3.9 shows that the coefficients on this variable are significantly positive at the 1% level. The coefficient on Change Firm×Post SFAS 131 is -0.0263 (t-statistic=-2.45), and the coefficient on Change Firm×Post SFAS 131×High E-index is -0.0379 (t-statistic=-2.65).[71] This means that for change firms with a high E-index during the pre-SFAS 131 period, their use of trade credit decreases by 6.42 (=3.79+ 2.63) percentage points, whereas the use of trade credit decreases by 2.63 percentage points for change firms with a low E-index during the pre-SFAS 131 period. These results indicate that the reduction in the use of trade credit is greater for change firms with weak governance before the adoption of SFAS 131.

Overall, the results reported in Table 3.9 are consistent with "H4", suggesting that the effect of SFAS 131 is more pronounced among change firms with weaker governance mechanisms during the pre-SFAS 131 period. This finding supports the idea that firms with weaker governance have more opportunities to conceal private information (Chiang and Venkatesh, 1988; Boone and White, 2015), and the adoption of SFAS 131 may increase the incentive of these firms to disseminate private information, which, in turn, reduces information asymmetry and improves their access to financing.

[Insert Table 3.9 here]

3.5.4.4 Audit Quality

Our final cross-sectional test examines whether the impact of the adoption of SFAS 131 on the use of trade credit varies with firms' quality of external auditing.

[71] The number of observations is smaller when we use the E-index as proxy for corporate governance, due to the availability of the data. We obtain the data from Lucien Bebchuk's website on the entrenchment index: http://www.law.harvard.edu/faculty/bebchuk/data.shtml.

The final hypothesis, "H5", implies that the effect of SFAS 131 on the use of trade credit is greater for change firms audited by non-Big 4 auditors during the pre-SFAS 131 period. To test this prediction, we construct an indicator variable, Non-Big 4 Auditor, which takes a value of one for firms that are not audited by Big 4 audit firms (i.e., Ernst & Young, Deloitte, KPMG, and PricewaterhouseCoopers) during the pre-SFAS 131 period (one year before the adoption of SFAS 131) and zero otherwise. Also, as in the cross-sectional tests above, we add the interaction terms of Change Firm×Post SFAS 131×Non-Big 4 Auditor and Non-Big 4 Auditor×Post SFAS 131 to Equation 3.1, allowing us to test the triple interaction effect. In this test, the coefficient on Change Firm×Post SFAS 131 captures the incremental change in use of trade credit for change firms audited by Big 4 auditors, and the coefficient on Change Firm×Post SFAS 131×Non-Big 4 Auditor captures the incremental change in the use of trade credit for change firms audited by non-Big 4 auditors during the pre-SFAS 131 period relative to those audited by Big 4 auditors. The variable of interest is Change Firm×Post SFAS 131×Non-Big 4 Auditor. Based on "H5", we expect the coefficient on Change Firm×Post SFAS 131×Non-Big 4 Auditor to be negative.

Table 3.10 reports the results for the cross-sectional test based on auditing quality. The table shows that the coefficient on Change Firm×Post SFAS 131×Non-Big 4 Auditor is negative and significant at the 5% level. In particular, the coefficient on Change Firm×Post SFAS 131 is -0.0145 (t-statistic=-2.27), and the coefficient on Change Firm×Post SFAS 131×Non-Big 4 Auditor is -0.0087 (t-statistic=-2.24). This indicates that for change firms audited by non-Big 4 audit firms, their use of trade credit decreases by 2.32 (=1.45 + 0.87) percentage points, while the use of trade credit decreases by 1.45 percentage points for change firms audited by Big 4 audit firms. These results are consistent with "H5", suggesting that the reduction in the use of trade credit is more pronounced for change firms audited by non-Big 4 audit firms during the pre-SFAS 131 period. This finding is consistent with the view that change firms audited by non-Big 4 audit firms during the per-SFAS 131 period may generate less credible financial reporting relative to change firms audited by Big 4 audit firms. The adoption of SFAS 131 improves firms' information environment, which, in turn, improves their access to financing and, thereby, enables them to rely less on trade credit.

In summary, consistent with the conjecture that the adoption of SFAS 131 decreases firms' use of trade credit through improving their information environment and reducing information asymmetry, we find that the effect of SFAS 131 on the use of trade credit is more pronounced in change firms with high ex-ante default risk, high information opacity, weak corporate governance, and low auditing quality (with non-Big 4 auditors). The observed reduction in the use of trade credit is because of the reduction in a firm's information asymmetry after the adoption of SFAS 131 that gives firms easier and access to cheaper sources of financing. To uncover whether the adoption of SFAS 131 actually improves a firm's access to financing, in the next subsection, we provide more evidence of whether the adoption of SFAS 131 affects the firm's financial constraints and financing behaviours.

[Insert Table 3.10 here]

3.5.5 Further Analysis

Our results thus far show that the adoption of SFAS 131 decreases the use of trade credit through improving the firm's information environment, enabling firms to substitute the trade credit financing with more public information-sensitive financing sources (e.g., debt and equity financing). One may wonder whether the adoption of SFAS 131 affects firms' financial constraints and financing behaviours. In order to investigate these issues, we examine the impact of SFAS 131 on financial constraints, stock liquidity, equity issuance, and debt issuance.

3.5.5.1 Effect of the Adoption of SFAS 131 on Financial Constraints

In this subsection, we investigate whether the adoption of SFAS 131 reduces a firm's financial constraints. Table 3.11 presents the results. We use two measures of financial constraints widely used in the literature as a dependent variable, the WW index of Whited and Wu (2006) (in Column 1), and the HP index of Hadlock and Pierce (2010) (in Column 2). In both Columns (1) and (2), the results show that the coefficient on Change Firm×Post SFAS 131 is negative and significant at the 5% level (t-statistics=-2.31 and -2.50 respectively), indicating an incremental decrease in financial constraints for change firms after the adoption of SFAS 131. These results support the idea that the reduction in the use of trade credit for change firms after the adoption of SFAS 131 is because of the improvement in the firm's information environment and better access to sources of financing. In the next subsection, we further investigate the effects of the adoption of SFAS 131 on a firm's stock liquidity, equity and debt issuances.

[Insert Table 3.11 here]

3.5.5.2 Effect of the Adoption of SFAS 131 on Stock Liquidity and Equity and Debt Issuance

We now examine the impact of the adoption of SFAS 131 on the firm's stock liquidity, using the illiquidity measure proposed by Amihud (2002) as a dependent variable. Column (1) of Table 3.12 shows that the coefficient on Change Firm×Post SFAS 131 is negative and significant at the 5% level (t-statistic=-2.35), suggesting an incremental reduction in stock illiquidity (i.e., increase in stock liquidity) for change firms after the adoption of SFAS 131.[72] This result indicates that the adoption of SFAS 131 improves equity market accessibility through improved stock liquidity, which, in turn, leads the firm to rely less on trade credit. As documented by Shang (2020), firms with higher stock liquidity are less reliant on trade credit financing.

Having shown that the adoption of SFAS 131 decreases financial constraints and stock illiquidity, we next examine whether the adoption of SFAS 131 increases the firm's equity issuance and debt issuance. Given that we find that a reduction in the firm's financial constraints and stock illiquidity for change firms after the adoption of SFAS 131, we expect an increase in the firm's external financing for these firms in the post-SFAS 131. Column (2) of Table 3.12 presents the results of the impact of the adoption of SFAS 131 on net financing, following Butler et al. (2011), defined as the sum of net debt and net equity to total assets. Column (2) of Table 3.12 shows that Change Firm×Post SFAS 131 is positive and significant at the 10% level (t-statistic=1.86), suggesting that change firms raise more external capital in the post-SFAS 131 period relative to the pre-SFAS 131 period than no-change firms.

Moreover, we examine whether the adoption of SFAS 131 leads firms to increase their equity and/or debt issuance. For equity issuance, we follow McKeon (2015) and construct an indicator variable, Equity Issuance Dummy, which takes a value of one if the firm's sale of common and preferred stock is greater than or equal to 3% of its average year-begin and year-end market equity, and zero otherwise. We then

[72] These results are similar to those of Jayaraman and Wu (2019).

estimate a logistic regression model in which the dependent variable is Equity Issuance Dummy. For debt issuance, we follow Hovakimian (2006) and construct an indicator variable, Debt Issuance Dummy, which takes a value of one if the change in the total debt exceeds 5% of total assets, and zero otherwise. Again, we estimate a logistic regression model in which the dependent variable is Debt Issuance Dummy. Column (3) of Table 3.12 presents the result for the equity issuance. The coefficient on Change Firm×Post SFAS 131 is positive and significant at the 5% level (t-statistic=-1.78), indicating an incremental increase in net equity issuance for change firms after the adoption of SFAS 131. Column (4) of Table 3.12 presents the result for the impact of the adoption of SFAS 131 on debt issuance. We find that the coefficient on Change Firm×Post SFAS 131 is insignificant, indicating that the adoption of SFAS 131 does not significantly increase firms' debt issuance.

Overall, these results are consistent with the notion that the newly revealed information under SFAS 131 enhances market valuations and has a positive impact on the precision of investor beliefs about the firm's future earnings (Berger and Hann, 2003). It is expected that shareholders are the most sensitive to exogenous changes in the information environment caused by the adoption of SFAS 131 relative to debt holders and suppliers. Thus, it is not surprising that change firms issue more equity after the adoption of SFAS 131. In other words, change firms substitute less public information-sensitive financing (i.e., trade credit) with more public information-sensitive financing (i.e., equity). Moreover, the increase of equity financing in the change firms is consistent with the argument that the adoption of SFAS 131 reduces agency costs (Berger and Hann, 2003; Cho, 2015).

[Insert Table 3.12 here]

3.6 Conclusion

This study attempts to further our understanding of the impact of changes in the firm's information environment on the use of trade credit financing. While existing literature establishes a causal relationship between the use of trade credit and different information sources, such as analysts' coverage and financial reporting, this chapter extends the literature by examining the impact of segment reporting quality on the use of trade credit. More specifically, we investigate the effect of an exogenous change in the firm's information environment on a firm's use of trade credit, using the change in U.S. segment reporting rules from SFAS 14 to SFAS 131 as a quasi-natural experiment. We conjecture that the adoption of SFAS 131 makes firms reveal new information about their corporate diversification status, which allows capital market participants to better assess the firm's credit risk. As a result, firms that have revealed new information about their corporate diversification status can improve their access to sources of financing and, thereby, rely less on more expensive trade credit financing. Using a sample of 12,174 U.S. firm-year observations during the 1994–2002 period, we find strong evidence that the adoption of SFAS 131 significantly decreases the firm's use of trade credit financing.

We conduct a battery of tests to check the validity of our quasi-natural experiment and the robustness of our main findings. In support of a causal interpretation of our main finding, we show that the decrease in the use of trade credit occurs after the adoption of SFAS 131, but not before. We further show that the decrease in the use of trade credit is because of a decrease in information asymmetry with respect to the firm's true underlying diversification, rather than increased information disaggregation at the segment level. In addition, our results are robust to an alternative control group, observable differences in firm characteristics, additional fixed effects, alternative estimation windows, and alternative measures of trade credit.

Moreover, we add credence to our main hypothesis that the negative impact of SFAS 131 adoption on the use of trade credit is primarily driven by the improvement in the firm's information environment by providing cross-sectional analyses. More specifically, we demonstrate that the effect of the adoption of SFAS 131 on the use of trade credit is more pronounced for change firms with greater default risk, more opaque information environments, weaker corporate governance, and non-Big 4 auditors during the pre-SFAS 131 period.

Our empirical results suggest that the exogenous change in the firm's information environment caused by the adoption of SFAS 131 improves the firm's access to other sources of financing. Consequently, the adoption of SFAS 131 leads firms to substitute trade credit with other cheaper sources of financing (i.e., equity) that are more information-sensitive. Further analyses show that the adoption of SFAS 131 improves the firm's access to sources of financing. In particular, we show that the adoption of SFAS 131 decreases firms' financial constraints and stock illiquidity. Moreover, we show that the adoption of SFAS 131 allows firms to raise more external capital. Specifically, firms that revealed new information about their corporate diversification status upon the adoption of SFAS 131 tend to issue more equity financing. Taken together, these findings are consistent with the view that the adoption of SFAS 131 affects the firm's market valuation and provides investors with better information about the firm's diversification activities, which in turn shapes the firm's financing choices.

Tables-Chapter 3

Table 3.1. Descriptive Statistics and Correlations

Table 3.1 presents the descriptive statistics and correlations. Panel A presents the descriptive statistics of variables used in our analysis using a window of four years before and after the adoption of SFAS 131. Panel B presents the Pearson correlation coefficients of variables. All variables are defined in the Appendix.

Panel A: Descriptive Statistics

	N	Mean	Std.dev.	p1	p25	Median	p75	p99
Change Firm	12174	0.203	0.402	0.000	0.000	0.000	0.000	1.000
Post SFAS 131	12174	0.493	0.500	0.000	0.000	0.000	1.000	1.000
AP/TA	12174	0.094	0.081	0.006	0.039	0.070	0.122	0.439
Firm size	12174	4.753	1.842	-0.074	3.505	4.756	6.004	9.439
Tangibility	12174	0.275	0.228	0.0157	0.093	0.203	0.391	0.902
Cost of Goods Sold	12174	0.864	0.713	0.032	0.363	0.696	1.145	3.846
Negative Growth	12174	-0.040	0.105	-0.584	0.000	0.000	0.000	0.000
Positive Growth	12174	0.323	0.654	0.000	0.003	0.128	0.340	4.849
R&D	12174	0.068	0.127	0.000	0.000	0.001	0.089	0.727
ROA	12174	-0.038	0.249	-1.319	-0.050	0.034	0.083	0.254
MTB	12174	2.360	2.601	0.583	1.083	1.575	2.655	12.330
Cash Holding	12174	0.202	0.233	0.000	0.021	0.097	0.324	0.893
Leverage	12174	0.200	0.208	0.000	0.011	0.144	0.330	0.916
Market Share	12174	0.002	0.006	0.000	0.000	0.000	0.001	0.041
Number of segments	12174	1.131	0.450	1.000	1.000	1.000	1.000	3.000

	Panel B: Correlation Matrix															
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	Change Firm	1.00														
(2)	Post SFAS 131	-0.02	1.00													
(3)	AP/TA	-0.00	-0.03	1.00												
(4)	Firm size	0.20	0.07	0.15	1.00											
(5)	Tangibility	-0.01	-0.00	-0.10	0.18	1.00										
(6)	Cost of Goods Sold	0.04	-0.02	0.53	0.32	-0.01	1.00									
(7)	Negative Growth	0.04	-0.13	0.01	0.26	0.08	0.07	1.00								
(8)	Positive Growth	-0.06	-0.11	-0.064	-0.19	-0.08	-0.13	0.18	1.00							
(9)	R&D	-0.13	0.02	-0.08	-0.42	-0.27	-0.22	-0.25	0.17	1.00						
(10)	ROA	0.08	-0.093	-0.10	0.44	0.09	0.06	0.40	-0.12	-0.58	1.00					
(11)	MTB	-0.09	-0.01	-0.06	-0.15	-0.18	-0.16	-0.00	0.25	0.35	-0.17	1.00				
(12)	Cash Holding	-0.16	-0.03	-0.28	-0.42	-0.42	-0.33	-0.17	0.25	0.51	-0.23	0.37	1.00			
(13)	Leverage	0.08	0.07	0.03	0.17	0.35	0.06	0.02	-0.04	-0.22	-0.09	-0.18	-0.43	1.00		
(14)	Market Share	0.16	0.01	0.00	0.51	0.12	0.07	0.07	-0.08	-0.14	0.13	-0.03	-0.18	0.12	1.00	
(15)	Number of segments	0.61	0.30	-0.02	0.14	-0.00	0.01	0.00	-0.06	-0.09	0.03	-0.08	-0.12	0.09	0.12	1.00

Table 3.2. Univariate Analysis

This table presents the univariate analysis on the use of trade credit and other firm characteristics in the pre-and-post SFAS 131 periods of change firms and no-change firms. Change firms are firms that disclosed a single segment before the adoption of SFAS 131 and were forced to reveal their previously hidden diversification status upon the adoption of SFAS 131. No-change firms are firms that disclosed a single segment before and after the adoption of SFAS 131.

	Pre-SFAS 131 Period				Post-SFAS 131 Period					
	(1) Change firm (N=1,310)	(2) No-change firm (N=4,862)	(3) Difference.		(4) Change firm (N=1,163)	(5) No-change firm (N=4,839)	(6) Difference.		(7) Diff. in Diff.	
	Mean	Mean	Diff.	t-stat.	Mean	Mean	Diff.	t-stat.	Diff.	t-stat.
AP/TA	0.098	0.097	0.001	0.18	0.088	0.093	-0.005	-1.30	-0.006	-2.06
Firm size	5.368	4.412	0.956	9.49	5.637	4.717	0.920	9.16	-0.036	0.63
Tangibility	0.269	0.279	-0.010	-0.84	0.269	0.273	-0.004	-0.38	0.006	0.72
Cost of Goods Sold	0.967	0.859	0.108	2.56	0.883	0.837	0.046	1.14	-0.062	-2.45
Negative Growth	-0.016	-0.028	0.012	5.56	-0.045	-0.057	0.012	3.02	0.000	0.05
Positive Growth	0.283	0.425	-0.142	-6.79	0.182	0.264	-0.082	-5.40	0.060	2.86
R&D	0.038	0.073	-0.035	-6.88	0.033	0.081	-0.049	-10.30	-0.014	-4.01
MTB	2.503	2.045	-0.458	-5.19	1.691	2.463	-0.772	-8.51	-0.314	-3.56
ROA	0.023	-0.025	0.048	6.03	-0.014	-0.073	0.059	5.78	0.011	1.14
Cash Holding	0.138	0.229	-0.091	-9.07	0.113	0.215	-0.102	-10.37	-0.011	-1.38
Leverage	0.213	0.177	0.036	3.50	0.259	0.206	0.053	4.39	0.017	1.78
Market Share	0.005	0.002	0.003	5.40	0.005	0.002	0.003	5.02	0.000	0.17
Number of segments	1.019	1.000	0.019	3.19	2.353	1.000	1.353	41.58	1.334	40.91

Table 3.3. Baseline Evidence: Effect of the Adoption of SFAS 131 on the Use of Trade Credit

This table presents results using a difference-in-differences (DiD) of the effect of the change in the information environment on the use of trade credit, using the adoption of SFAS 131 as a quasi-natural experiment. The dependent variable is the ratio of accounts payable to total assets. Change Firm is an indicator variable equal to one for firms reported as single-segment firms under SFAS 14 but revealed previously hidden information about their industry operations (diversification status) upon adoption of SFAS 131, and zero otherwise. Post SFAS 131 is an indicator variable equal to one for the Post-adoption period, and zero otherwise. Regressions in Columns (1) and (2) include Fama-French 48 industry and year fixed effects. Regressions in Columns (3) and (4) include firm and year fixed effects. Coefficient estimates for Change Firm in Columns (3) and (4) are suppressed because of firm fixed effects. Standard errors are clustered at the firm level (in brackets). $*$, $**$, and $***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variable definitions and sources of data are described in the Appendix.

	[1] AP/TA	[2] AP/TA	[3] AP/TA	[4] AP/TA
Change Firm × Post SFAS 131	-0.0069***	-0.0125**	-0.0061***	-0.0178***
	(-2.61)	(-1.99)	(-2.67)	(-2.91)
Change firm	-0.0021	-0.0091**		
	(-0.54)	(-2.55)		
Post SFAS 131	-0.0008	-0.0010	0.0066***	0.0028
	(-0.21)	(-0.31)	(3.27)	(1.56)
Firm size		0.0003		-0.0028*
		(0.22)		(-1.81)
Tangibility		-0.0646***		-0.0254**
		(-7.15)		(-2.58)
Cost of Goods Sold		0.0476***		0.0436***
		(12.91)		(12.46)
Negative Growth		0.0260***		0.0246***
		(3.26)		(3.85)
Positive Growth		-0.0002		0.0002
		(-0.24)		(0.22)
R&D		-0.0327**		0.0273**
		(-2.33)		(2.07)
ROA		-0.0796***		-0.0365***
		(-12.09)		(-7.84)
MTB		0.0015***		0.0016***
		(3.17)		(4.45)
Cash Holding		-0.0957***		-0.0737***
		(-13.06)		(-11.04)
Leverage		-0.0298***		-0.0045
		(-4.33)		(-0.82)
Market Share		0.2689		-0.2567
		(1.18)		(-1.05)
Number of Segments		0.0203		0.0312***
		(1.64)		(2.72)
Intercept	0.0546***	0.0569***	0.0999***	0.0694***
	(4.40)	(4.11)	(64.65)	(5.56)
N	12174	12174	12174	12174
R^2	0.1777	0.4263	0.0084	0.2095
Industry effects	Yes	Yes	No	No
Firm effects	No	No	Yes	Yes
Year effects	Yes	Yes	Yes	Yes

Table 3.4. The Timing of Changes in Firms' Use of Trade Credit Around the Adoption of SFAS 131

This table presents evidence about the timing of changes in the use of trade credit around the adoption of SFAS 131. The dependent variable is the ratio of accounts payable to total assets. Change Firm is an indicator variable equal to one for firms reported as single-segment firms under SFAS 14 but revealed previously hidden information about their industry operations (diversification status) upon adoption of SFAS 131, and zero otherwise. Panel A presents results for parallel trends and persistence tests. Before(-1) (Before(-2)) is an indicator variable that equals one for firm-year observations, one year (two years) before the adoption of SFAS 131, and zero otherwise. Post SFAS 131 is an indicator variable equal to one for the Post-adoption period, and zero otherwise. After(+1,+2) is an indicator variable that equals one for firm-year observations during the two-year period after the adoption of SFAS 131, and zero otherwise. After (+3,+4) equals one for firm-year observations in the year 3 and after the adoption of SFAS 131, and zero otherwise. Coefficient estimates on the main effects of Before(-1), Before(-2), After(+1,+2), and After (+3,+4) have been omitted for brevity. Panel B presents the results of dynamic difference-in-differences (DiD) estimations that verify the parallel trend assumption and identify the timing of the SFAS 131 effect. This panel extends our DiD model in Table 3.2 by replacing the single Post SFAS 131 indicator with event-year specific indicators T, where T_n is a variable equal to one if a year is the n-th year after/before the adoption of SFAS 131. All regressions in both panels, A and B, include firm and year fixed effects and include the same control variables used in Table 3.2. The coefficient estimates for Change Firm are suppressed because of firm fixed effects. Standard errors are clustered at the firm level (in brackets). $*$, $**$, and $***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variable definitions and sources of data are described in the Appendix.

Panel A: Parallel trends and persistence test

	Parallel Trends Test		Persistence Test
	[1]	[2]	[3]
	AP/TA	AP/TA	AP/TA
Change Firm × Before(-2)		0.0000	
		(0.01)	
Change Firm × Before(-1)	-0.0028		
	(-1.26)		
Change Firm × Post SFAS 131	-0.0185***	-0.0178***	
	(-2.98)	(-2.74)	
Change Firm × After(+1,+2)			-0.0159***
			(-2.65)
Change Firm × After(+3,+4)			-0.0193***
			(-3.05)
Intercept	0.0696***	0.0694***	0.0703***
	(5.57)	(5.56)	(5.65)
N	12174	12174	12174
R^2	0.2096	0.2096	0.2097
Firm effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Panel B: Dynamic Difference-in-Differences Estimations	
	[1] AP/TA
Change Firm × T_{-3}	-0.0017
	(-0.70)
Change Firm × T_{-2}	0.0014
	(0.44)
Change Firm × T_{-1}	-0.0027
	(-0.82)
Change Firm × T_{+1}	-0.0167**
	(-2.41)
Change Firm × T_{+2}	-0.0174**
	(-2.53)
Change Firm × T_{+3}	-0.0212***
	(-2.87)
Change Firm × T_{+4}	-0.0189***
	(-2.66)
T_{-3}	0.0020
	(0.17)
T_{-2}	0.0102
	(0.44)
T_{-1}	0.0191
	(0.56)
T_{+1}	0.0286
	(0.63)
T_{+2}	0.0347
	(0.61)
T_{+3}	0.0446
	(0.66)
T_{+4}	0.0558
	(0.70)
Intercept	0.0721***
	(5.98)
N	12174
R^2	0.2109
Firm effects	Yes
Year effects	Yes
Controls	Yes

Table 3.5. Placebo Test

This table presents the results of the additional analyses, the purpose of which is to test whether more disaggregated information at the segment level instead of revealed diversification status could explain the change in the use of trade credit. This table replaces our change firms with a group of firms (placebo group) that reveal an increased number of operating segments through the adoption of SFAS 131 while still operating in a single industry(i.e., firms that operate in the same four-digit SIC code industry over the sample period). The dependent variable is the ratio of accounts payable to total assets. Placebo is an indicator variable equal to one for firms that reveal an increased number of operating segments under SFAS 131 while still operating in a single industry and 0 otherwise. Post SFAS 131 is an indicator variable equal to one for the Post-adoption period, and zero otherwise. All regressions (1-2) include firm and year fixed effects. Coefficient estimates for Placebo are suppressed because of firm fixed effects. Standard errors are clustered at the firm level (in brackets). ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variable definitions and sources of data are described in the Appendix.

	[1] AP/TA	[2] AP/TA
Placebo × Post SFAS 131	-0.0015	-0.0007
	(-0.53)	(-0.28)
Post SFAS 131	0.0046**	0.0005
	(2.19)	(0.29)
Firm size		-0.0041***
		(-2.70)
Tangibility		-0.0259**
		(-2.50)
Cost of Goods Sold		0.0443***
		(12.99)
Negative Growth		0.0303***
		(4.78)
Positive Growth		0.0003
		(0.35)
R&D		0.0274**
		(2.11)
ROA		-0.0360***
		(-8.05)
MTB		0.0014***
		(3.91)
Cash Holding		-0.0743***
		(-11.07)
Leverage		0.0006
		(0.10)
Market Share		0.0089
		(0.26)
Intercept	0.0996***	0.0960***
	(62.90)	(11.43)
N	11142	11142
R^2	0.0071	0.2148
Firm effects	Yes	Yes
Year effects	Yes	Yes

Table 3.6. Robustness Tests

Panel A: Alternative Control Group

This table presents the results of the additional analyses, the purpose of which is to ensure that the control group does not include firms that strategically decided to remain no-change firms. The table presents the results for the alternative control group; that is, it replaces our control group with multi-segment firms that report the same number of segments before and after the reform. (as in Cho (2015)). The dependent variable is the ratio of accounts payable to total assets. Change Firm is an indicator variable equal to one for firms reported as single-segment firms under SFAS 14 but revealed previously hidden information about their industry operations (diversification status) upon adoption of SFAS 131, and zero otherwise. Post SFAS 131 is an indicator variable equal to one for the Post-adoption period, and zero otherwise. Column (1) presents results where multi-segment firms that report the same number of segments before and after the reform are our control group sample (i.e., no-change firms). Column (2) presents results, including multi-segment no-change firms and single-segment no-change firms in our control group sample. All regressions (1-2) include firm and year fixed effects. Coefficient estimates for Change Firm are suppressed because of firm fixed effects. Standard errors are clustered at the firm level (in brackets). $*$, $**$, and $***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variable definitions and sources of data are described in the Appendix.

	[1] AP/TA	[2] AP/TA
Change Firm × Post SFAS 131	-0.0103**	-0.0089**
	(-2.11)	(-2.02)
Post SFAS 131	0.0067**	0.0022
	(2.25)	(1.38)
Firm size	0.0004	-0.0033**
	(0.13)	(-2.25)
Tangibility	-0.0180	-0.0251***
	(-1.26)	(-2.76)
Cost of Goods Sold	0.0414***	0.0442***
	(6.71)	(13.71)
Negative Growth	0.0104	0.0231***
	(0.87)	(3.90)
Positive Growth	0.0037	0.0007
	(1.58)	(0.82)
R&D	-0.0006	0.0255**
	(-0.02)	(1.99)
ROA	-0.0382***	-0.0365***
	(-3.41)	(-8.09)
MTB	0.0014	0.0016***
	(1.50)	(4.61)
Cash Holding	-0.0676***	-0.0747***
	(-5.77)	(-11.86)
Leverage	-0.0223**	-0.0059
	(-2.53)	(-1.15)
Market Share	0.0232	0.0230
	(0.50)	(0.73)
Number of segments	0.0126*	0.0122
	(1.68)	(1.60)
Intercept	0.0641***	0.0827***
	(3.18)	(8.09)
N	4218	13983
R^2	0.1866	0.2082
Firm effects	Yes	Yes
Year effects	Yes	Yes

Panel B: Matched Difference-in-Differences (DiD) Regression

This table presents the results of the additional analyses in which change firms are matched with no-change firms based on one-to-one propensity score matching with replacement in Column (1) and without replacement in Column (2). Propensity scores are obtained from a logit regression of change-firm on a set of matching variables including Firm Size, Tangibility, MTB, Leverage, R&D, ROA, Cash Holding, Negative Growth, Positive Growth, Market Share and Fama French (48) industry dummies. The dependent variable is the ratio of accounts payable to total assets. Change Firm is an indicator variable equal to one for firms reported as single-segment firms under SFAS 14 but revealed previously hidden information about their industry operations (diversification status) upon adoption of SFAS 131, and zero otherwise. Post SFAS 131 is an indicator variable equal to one for the Post-adoption period, and zero otherwise. All regressions (1-2) include firm and year fixed effects. Coefficient estimates for Change Firm are suppressed because of firm fixed effects. Standard errors are clustered at the firm level (in brackets). $*$, $**$, and $***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variable definitions and sources of data are described in the Appendix.

	[1] AP/TA	[2] AP/TA
Change Firm × Post SFAS 131	-0.0221***	-0.0205***
	(-3.26)	(-2.91)
Post SFAS 131	0.0051*	0.0045
	(1.65)	(1.46)
Firm size	0.0004	0.0011
	(0.13)	(0.34)
Tangibility	-0.0065	-0.0094
	(-0.39)	(-0.56)
Cost of Goods Sold	0.0381***	0.0368***
	(7.05)	(6.36)
Negative Growth	0.0151	0.0172
	(1.22)	(1.48)
Positive Growth	0.0024	0.0027
	(1.24)	(1.55)
R&D	0.0055	0.0098
	(0.19)	(0.37)
ROA	-0.0359***	-0.0365***
	(-3.63)	(-3.96)
MTB	0.0026**	0.0034***
	(2.29)	(3.39)
Cash Holding	-0.0818***	-0.0807***
	(-7.18)	(-7.30)
Leverage	-0.0196**	-0.0214**
	(-2.05)	(-2.38)
Market Share	-0.6231*	-0.6567**
	(-1.94)	(-1.97)
Number of segments	0.0378***	0.0375***
	(2.97)	(2.78)
Intercept	0.0525**	0.0522**
	(2.48)	(2.37)
N	4209	3874
R^2	0.2004	0.2009
Firm effects	Yes	Yes
Year effects	Yes	Yes
Replacement	Yes	No

Panel C: Additional Fixed Effects

This table presents the results of the additional analyses, the purpose of which is to ensure our results are robust to industry-year (Column 1) and industry-year and state-year fixed effects (Column 2). State-year fixed effects are based on the location of the firm's headquarters. Industry-year fixed effects are based on Fama-French 48 industry definitions. The dependent variable is the ratio of accounts payable to total assets. Change Firm is an indicator variable equal to one for firms reported as single-segment firms under SFAS 14 but revealed previously hidden information about their industry operations (diversification status) upon adoption of SFAS 131, and zero otherwise. Post SFAS 131 is an indicator variable equal to one for the Post-adoption period, and zero otherwise. All regressions (1-2) include firm fixed effects. Coefficient estimates for Change Firm are suppressed because of firm fixed effects. Standard errors are clustered at the firm level (in brackets). ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variable definitions and sources of data are described in the Appendix.

	[1] AP/TA	[2] AP/TA
Change Firm × Post SFAS 131	-0.0169***	-0.0172**
	(-2.60)	(-2.56)
Post SFAS 131	0.0021	0.0020
	(1.15)	(1.05)
Firm size	-0.0022	-0.0025
	(-1.37)	(-1.47)
Tangibility	-0.0244**	-0.0230**
	(-2.37)	(-2.19)
Cost of Goods Sold	0.0434***	0.0427***
	(12.43)	(12.23)
Negative Growth	0.0205***	0.0216***
	(3.10)	(3.19)
Positive Growth	-0.0001	-0.0002
	(-0.15)	(-0.21)
R&D	0.0267*	0.0268*
	(1.94)	(1.94)
ROA	-0.0386***	-0.0385***
	(-7.97)	(-7.83)
MTB	0.0016***	0.0015***
	(4.06)	(4.00)
Cash Holding	-0.0744***	-0.0752***
	(-10.86)	(-10.76)
Leverage	-0.0050	-0.0046
	(-0.90)	(-0.82)
Market Share	-0.4737	-0.5290
	(-1.53)	(-1.64)
Number of Segments	0.0286**	0.0298**
	(2.35)	(2.37)
Intercept	0.0695***	0.0704***
	(5.42)	(5.46)
N	12174	12174
R^2	0.2372	0.2625
Firm effects	Yes	Yes
Industry ×Year effects	Yes	Yes
State ×Year effects	No	Yes

Panel D: Different Estimation Windows

This table presents results for the additional robustness checks when considering different sample periods. The dependent variable is the ratio of accounts payable to total assets. Change Firm is an indicator variable equal to one for firms reported as single-segment firms under SFAS 14 but revealed previously hidden information about their industry operations (diversification status) upon adoption of SFAS 131, and zero otherwise. Post SFAS 131 is an indicator variable equal to one for the Post-adoption period, and zero otherwise. Column (1) presents results for a window of five years before/after the adoption of SFAS 131. Column (2) presents results for a window of three years before/after the adoption of SFAS 131. All regressions (1-2) include firm and year fixed effects. Coefficient estimates for Change Firm are suppressed because of firm fixed effects. Standard errors are clustered at the firm level (in brackets). ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variable definitions and sources of data are described in the Appendix.

	[1] AP/TA	[2] AP/TA
Change Firm × Post SFAS 131	-0.0153***	-0.0139**
	(-2.73)	(-2.44)
Post SFAS 131	0.0027	0.0024
	(1.43)	(1.43)
Firm size	-0.0029**	-0.0039**
	(-2.03)	(-2.25)
Tangibility	-0.0280***	-0.0248**
	(-3.10)	(-2.14)
Cost of Goods Sold	0.0429***	0.0415***
	(14.14)	(10.36)
Negative Growth	0.0191***	0.0268***
	(3.43)	(3.53)
Positive Growth	0.0004	0.0004
	(0.52)	(0.49)
R&D	0.0332***	0.0334**
	(2.73)	(2.18)
ROA	-0.0325***	-0.0375***
	(-7.93)	(-6.83)
MTB	0.0016***	0.0016***
	(4.57)	(4.01)
Cash Holding	-0.0765***	-0.0753***
	(-12.29)	(-10.55)
Leverage	-0.0029	-0.0068
	(-0.55)	(-1.17)
Market Share	0.0461	-0.0152
	(0.97)	(-0.27)
Number of Segments	0.0298***	0.0240**
	(2.75)	(2.26)
Intercept	0.0682***	0.0795***
	(6.10)	(6.00)
N	14077	9990
R^2	0.2069	0.2068
Firm effects	Yes	Yes
Year effects	Yes	Yes

Panel E. Alternative Measures of Trade Credit

This table presents the results of the additional analyses, the purpose of which is to ensure our results are robust to alternative ways of defining the use of trade credit. Column (1) presents results for the dependent variable accounts payable, scaled by the cost of goods sold. Column (2) presents results for the dependent variable accounts payable, scaled by sales. Change Firm is an indicator variable equal to one for firms reported as single-segment firms under SFAS 14 but revealed previously hidden information about their industry operations (diversification status) upon adoption of SFAS 131, and zero otherwise. Post SFAS 131 is an indicator variable equal to one for the Post-adoption period, and zero otherwise. All regressions (1-2) include firm and year fixed effects. Coefficient estimates for Change Firm are suppressed because of firm fixed effects. Standard errors are clustered at the firm level (in brackets). ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variable definitions and sources of data are described in the Appendix.

	[1] AP/COGS	[2] AP/SALE
Change Firm × Post SFAS 131	-0.0358***	-0.0229**
	(-2.83)	(-2.45)
Post SFAS 131	-0.0064	-0.0055
	(-0.95)	(-1.32)
Firm size	-0.0384***	-0.0860***
	(-5.56)	(-11.69)
Tangibility	-0.0155	-0.0673***
	(-0.36)	(-2.58)
Cost of Goods Sold	-0.1033***	-0.0105**
	(-10.87)	(-2.04)
Negative Growth	-0.0188	-0.0636***
	(-0.74)	(-2.91)
Positive Growth	0.0096*	-0.0055
	(1.77)	(-1.47)
R&D	0.0746	-0.0375
	(1.40)	(-0.72)
ROA	-0.0099	-0.0453***
	(-0.60)	(-3.80)
MTB	0.0038***	0.0019**
	(2.68)	(1.96)
Cash Holding	-0.0444	-0.0679***
	(-1.54)	(-3.41)
Leverage	-0.0066	0.0068
	(-0.31)	(0.53)
Market Share	1.4137**	5.3957***
	(2.20)	(6.51)
Number of Segments	0.0895***	0.0592***
	(3.74)	(3.12)
Intercept	0.3634***	0.4774***
	(9.08)	(12.32)
N	12174	12174
R^2	0.0670	0.2015
Firm effects	Yes	Yes
Year effects	Yes	Yes

Table 3.7. Cross-Sectional Analysis: The Role of Ex-Ante Default Risk

This table presents the results of the cross-sectional analysis of the use of trade credit, which focuses on the role of the default risk experienced by firms during the pre-SFAS 131 period. Column (1) reports the results when ex-ante default risk is proxied by Ohlson's (1980) O-score. Ohlson is an indicator variable that takes a value of one if the firm's Ohlson probability of bankruptcy is greater than 50% during the pre-SFAS 131 period (during t-1) and zero otherwise. Column (2) reports the results when ex-ante default risk is proxied by Altman's (1980) Z-score. Altman is an indicator variable that takes a value of one if the firm's Altman Z score of bankruptcy is below 1.81 during the pre-SFAS 131 period (during t-1) and zero otherwise. The total impact of SFAS 131 on change firms (relative to no-change firms) with Ohlson (Altman) = 0 is captured by the coefficient on Change Firm × Post 131. The total impact of SFAS 131 on change firms (relative to no-change firms) with Ohlson (Altman)= 1 is the sum of the coefficients on Change Firm × Post 131 and Change Firm × Post 131 × Ohlson (Altman). Regressions in Columns (1) and (2) include firm and year fixed effects. Standard errors are clustered at the firm level (in brackets). $*$, $**$, and $***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variable definitions and sources of data are described in the Appendix.

	[1] AP/TA	[2] AP/TA
Change Firm × Post SFAS 131	-0.0172^{***}	-0.0164^{***}
	(-2.76)	(-2.65)
Change Firm × Post SFAS 131 × Ohlson	-0.0125^{**}	
	(-2.26)	
Post SFAS 131 × Ohlson	0.0087^{***}	
	(2.74)	
Change Firm × Post SFAS 131 × Altman		-0.0101^{*}
		(-1.69)
Post SFAS 131 × Altman		0.0090^{***}
		(2.71)
Post SFAS 131	0.0000	0.0014
	(0.02)	(0.76)
Firm size	-0.0030^{*}	-0.0029^{*}
	(-1.87)	(-1.92)
Tangibility	-0.0287^{***}	-0.0242^{**}
	(-2.82)	(-2.46)
Cost of Goods Sold	0.0419^{***}	0.0432^{***}
	(11.65)	(12.21)
Negative Growth	0.0287^{***}	0.0247^{***}
	(4.42)	(3.87)
Positive Growth	0.0004	0.0002
	(0.47)	(0.22)
R&D	0.0250^{*}	0.0272^{**}
	(1.81)	(2.07)
ROA	-0.0377^{***}	-0.0371^{***}
	(-7.93)	(-8.04)
MTB	0.0015^{***}	0.0016^{***}
	(4.07)	(4.40)
Cash Holding	-0.0751^{***}	-0.0739^{***}
	(-10.87)	(-11.07)
Leverage	-0.0084	-0.0055
	(-1.47)	(-1.00)
Market Share	0.0618	0.0375
	(0.62)	(0.43)
Number of Segments	0.0354^{***}	0.0315^{***}
	(3.03)	(2.73)
Intercept	0.0711^{***}	0.0694^{***}
	(5.54)	(5.56)
N	11310	12157
R^2	0.2023	0.2110
Firm effects	Yes	Yes
Year effects	Yes	Yes

Table 3.8. Cross-Sectional Analysis: The Role of Information Opacity

This table presents the results of the cross-sectional analysis of the use of trade credit, which focuses on the role of information opacity experienced by firms during the pre-SFAS 131 period. Column (1) reports the results when information opacity is proxied by the probability of informed trading (PIN). High PIN is an indicator variable that is equal to one for firms in the top quartile of the PIN distribution during the pre-SFAS 131 period (during t-1), and zero otherwise. Column (2) reports the results when information opacity is proxied by idiosyncratic risk (IR). High IR is an indicator variable that equal to one for firms in the top quartile of the idiosyncratic risk distribution during the pre-SFAS 131 period (during t-1), and zero otherwise. The total impact of SFAS 131 on change firms (relative to no-change firms) with High PIN(High IR) = 0 is captured by the coefficient on Change Firm × Post SFAS131. The total impact of SFAS 131 on change firms (relative to no-change firms) with High PIN(High IR) = 1 is the sum of the coefficients on Change Firm × Post SFAS 131 and Change Firm × Post SFAS 131 × High PIN(High IR). Regressions in Columns (1) and (2) include firm and year fixed effects. Standard errors are clustered at the firm level (in brackets). ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variable definitions and sources of data are described in the Appendix.

	[1] AP/TA	[2] AP/TA
Change Firm × Post SFAS 131	-0.0144**	-0.0157**
	(-2.29)	(-2.50)
Change Firm × Post SFAS 131× High PIN	-0.0134***	
	(-2.78)	
Post SFAS 131 × High PIN	0.0059**	
	(2.45)	
Change Firm × Post SFAS 131× High IR		-0.0111*
		(-1.80)
Post SFAS 131 × High IR		0.0056*
		(1.93)
Post SFAS 131	0.0012	0.0012
	(0.61)	(0.67)
Firm size	-0.0027*	-0.0026*
	(-1.76)	(-1.66)
Tangibility	-0.0249**	-0.0254**
	(-2.53)	(-2.52)
Cost of Goods Sold	0.0434***	0.0428***
	(12.39)	(11.90)
Negative Growth	0.0243***	0.0262***
	(3.81)	(4.05)
Positive Growth	0.0000	0.0003
	(0.04)	(0.31)
R&D	0.0273**	0.0201
	(2.06)	(1.51)
ROA	-0.0365***	-0.0386***
	(-7.84)	(-8.08)
MTB	0.0016***	0.0015***
	(4.45)	(4.36)
Cash Holding	-0.0734***	-0.0727***
	(-11.05)	(-10.83)
Leverage	-0.0045	-0.0073
	(-0.82)	(-1.29)
Market Share	0.0577	0.0598
	(0.60)	(0.61)
Number of Segments	0.0306***	0.0314***
	(2.63)	(2.66)
Intercept	0.0687***	0.0698***
	(5.49)	(5.47)
N	12174	11727
R^2	0.2108	0.2053
Firm effects	Yes	Yes
Year effects	Yes	Yes

Table 3.9. Cross-Sectional Analysis: The Role of Corporate Governance

Panel A: Results Based on Institutional Ownership

This table presents the results of the cross-sectional analysis of the use of trade credit, which focuses on the role of corporate governance that firms had during the pre-SFAS 131 period. Corporate governance is proxied by institutional ownership. In Column (1), we use the percentage of shares outstanding owned by institutions measure of institutional ownership (IO). Low IO is an indicator variable that takes a value of one for firms in the bottom quartile of the institutional ownership percentage distribution during the pre-SFAS 131 period (during t-1), and zero otherwise. In Column (2), we use the outside blockholders percentage measure of institutional ownership. No Blockholder is an indicator variable that takes a value of one for firms without institutional investors that hold at least a 5% ownership stake in the firm during the pre-SFAS 131 period (during t-1), and zero otherwise. The total impact of SFAS 131 on change firms (relative to no-change firms) with Low IO (No Blockholders) = 0 is captured by the coefficient on Change Firm × Post SFAS 131.The total impact of SFAS 131 on change firms (relative to no-change firms) with Low IO (No Blockholders) = 1 is the sum of the coefficients on Change Firm × Post SFAS 131 and Change Firm × Post SFAS 131 × Low IO (No Blockholders). Regressions in Columns (1) and (2) include firm and year fixed effects. Standard errors are clustered at the firm level (in brackets). ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variable definitions and sources of data are described in the Appendix.

	[1] AP/TA	[2] AP/TA
Change Firm × Post SFAS 131	-0.0151**	-0.0150**
	(-2.58)	(-2.56)
Change Firm × Post SFAS 131× Low IO	-0.0082*	
	(-1.83)	
Post SFAS 131 × Low IO	0.0017	
	(0.77)	
Change Firm × Post SFAS 131× No Blockholders		-0.0074*
		(-1.77)
Post SFAS 131 × No Blockholders		0.0022
		(1.08)
Post SFAS 131	0.0021	0.0018
	(1.07)	(0.90)
Firm size	-0.0030**	-0.0031**
	(-1.97)	(-1.99)
Tangibility	-0.0250**	-0.0250**
	(-2.54)	(-2.54)
Cost of Goods Sold	0.0435***	0.0436***
	(12.45)	(12.50)
Negative Growth	0.0244***	0.0245***
	(3.82)	(3.83)
Positive Growth	0.0002	0.0002
	(0.21)	(0.21)
R&D	0.0269**	0.0269**
	(2.04)	(2.04)
ROA	-0.0363***	-0.0363***
	(-7.83)	(-7.82)
MTB	0.0016***	0.0016***
	(4.45)	(4.45)
Cash Holding	-0.0736***	-0.0735***
	(-11.01)	(-10.99)
Leverage	-0.0044	-0.0045
	(-0.80)	(-0.82)
Market Share	0.0566	0.0490
	(0.59)	(0.48)
Number of Segments	0.0317***	0.0321***
	(2.74)	(2.75)
Intercept	0.0692***	0.0690***
	(5.54)	(5.49)
N	12174	12174
R^2	0.2099	0.2099
Firm effects	Yes	Yes
Year effects	Yes	Yes

Panel B: Results Based on Entrenchment Index (E index)

This table presents the results of the cross-sectional analysis of the use of trade credit, which focuses on the role of corporate governance that firms had during the pre-SFAS 131 period. Corporate governance is proxied by the entrenchment index (E-index) obtained from Bebchuk et al. (2009). High E-index is an indicator variable that takes a value of one for firms in the top quartile of the E-index distribution during the pre-SFAS 131 period (during t-1) and zero otherwise. The total impact of SFAS 131 on change firms (relative to no-change firms) with High E-Index = 0 is captured by the coefficient on Change Firm × Post SFAS 131. The total impact of SFAS 131 on change firms (relative to no-change firms) with High E-Index = 1 is the sum of the coefficients on Change Firm × Post SFAS 131 and Change Firm × Post SFAS 131 × High E-Index. The regression includes firm and year fixed effects. Standard errors are clustered at the firm level (in brackets). ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variable definitions and sources of data are described in the Appendix.

	[1] AP/TA
Change Firm × Post SFAS 131	-0.0263**
	(-2.45)
Change Firm × Post SFAS 131× High E-index	-0.0379***
	(-2.65)
Post SFAS 131 × High E-index	0.0122*
	(1.77)
Post SFAS 131	0.0062
	(1.64)
Firm Size	-0.0097**
	(-2.09)
Tangibility	-0.0323
	(-1.20)
Cost of Goods Sold	0.0286***
	(3.10)
Negative Growth	0.0440***
	(3.73)
Positive Growth	0.0007
	(0.34)
R&D	0.0338
	(0.78)
ROA	-0.0202
	(-1.14)
MTB	0.0024***
	(2.64)
Cash holding	-0.0616***
	(-3.02)
Leverage	-0.0224
	(-1.29)
Market share	0.0816
	(0.45)
Number of Segments	0.0532***
	(2.76)
Intercept	0.1272***
	(3.17)
N	1163
R^2	0.2244
Firm effects	Yes
Year effects	Yes

Table 3.10. Cross-Sectional Analysis: The Role of Big 4 Auditors

This table presents the results of the cross-sectional analysis of the use of trade credit, which focuses on the role of Big 4 auditors during the pre-SFAS 131 period. Non-Big 4 auditor is an indicator variable that takes a value of one for firms that were not audited by Ernst & Young, Deloitte, KPMG, or PricewaterhouseCoopers during the pre-SFAS 131 period (during t-1), and zero otherwise. The total impact of SFAS 131 on change firms (relative to no-change firms) with Non-Big 4 Auditor = 0 is captured by the coefficient on Change Firm × Post 131. The total impact of SFAS 131 on change firms (relative to no-change firms) with Non-Big 4 Auditor = 1 is the sum of the coefficients on Change Firm × Post SFAS 131 and Change Firm × Post SFAS 131 × Non-Big 4 Auditor. The regression includes firm and year fixed effects. Standard errors are clustered at the firm level (in brackets). ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variable definitions and sources of data are described in the Appendix.

	[1] AP/TA
Change Firm × Post SFAS 131	-0.0145**
	(-2.27)
Change Firm × Post SFAS 131 × Non-Big 4 Auditor	-0.0087**
	(-2.24)
Post SFAS 131 × Non-Big-4 Auditor	0.0033
	(1.51)
Post SFAS 131	0.0016
	(0.88)
Firm size	-0.0030*
	(-1.95)
Tangibility	-0.0252**
	(-2.55)
Cost of Goods Sold	0.0436***
	(12.41)
Negative Growth	0.0245***
	(3.84)
Positive Growth	0.0001
	(0.17)
R&D	0.0267**
	(2.02)
ROA	-0.0365***
	(-7.87)
MTB	0.0016***
	(4.45)
Cash Holding	-0.0738***
	(-11.02)
Leverage	-0.0045
	(-0.82)
Market Share	0.0489
	(0.52)
Number of Segments	0.0314***
	(2.75)
Intercept	0.0695***
	(5.58)
N	12174
R^2	0.2101
Firm effects	Yes
Year effects	Yes

Table 3.11. Further Analysis: Effect of the Adoption of SFAS 131 on the Financial Constraints

This table presents results using a difference-in-differences (DiD) of the effect of the change in the information environment on financial constraints, using the adoption of SFAS 131 as a quasi-natural experiment. The dependent variable in Columns (1)-(2) is financial constraints. Financial constraints are measured using Whited and Wu (2006) index (WW) in Column (1) and Hadlock and Pierce (2010) index (HP) in Column (2). Change Firm is equal to one for firms reported as single-segment firms under SFAS 14 but revealed previously hidden information about their industry operations (diversification status) upon adoption of SFAS 131, and zero otherwise. Post SFAS 131 is a variable equal to one for the Post-adoption period, and zero otherwise. All regressions (1-2) include firm and year fixed effects. Coefficient estimates for Change Firm are suppressed because of firm fixed effects. Standard errors are clustered at the firm level (in brackets). ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variable definitions and sources of data are described in the Appendix.

	[1] WW Index	[2] HP Index
Change Firm × Post SFAS 131	-0.0101**	-0.0499**
	(-2.31)	(-2.50)
Post SFAS 131	0.0074***	0.0168***
	(3.37)	(3.13)
Firm Size	-0.0331***	-0.2103***
	(-17.69)	(-24.51)
Tangibility	0.0194*	0.1111**
	(1.74)	(2.50)
ROA	-0.1045***	-0.1256***
	(-21.82)	(-7.88)
MTB	-0.0002	0.0073***
	(-0.86)	(4.82)
Cash Holding	-0.0332***	-0.2338***
	(-4.90)	(-8.22)
Leverage	0.0018	-0.1464***
	(0.29)	(-6.95)
Number of Segments	0.0075	0.0903***
	(0.88)	(2.58)
Intercept	-0.0729***	-1.7886***
	(-6.47)	(-33.72)
N	12174	12174
R^2	0.3187	0.7259
Firm effects	Yes	Yes
Year effects	Yes	Yes

Table 3.12. Further Analysis: Effect of the Adoption of SFAS 131 on Stock Illiquidity and External Financing

This table presents results using a difference-in-differences (DiD) of the effect of the change in the information environment on stock illiquidity and external financing, using the adoption of SFAS 131 as a quasi-natural experiment. In Column (1), the dependent variable is stock illiquidity measured as in the Amihud (2002) measure of stock illiquidity. In Column (2), the dependent variable is net financing defined, following Butler et al. (2011), as the ratio of total capital raised (net equity plus net debt) to lagged assets. In Column (3), the dependent variable is the equity issuance dummy defined, following McKeon (2015), as an indicator variable equal to one if the firm's gross equity issuance (i.e., sale of common and preferred stock) is greater than or equal to 3% of its average year-begin and year-end market equity. In Column (4), the dependent variable is the debt issuance dummy defined, following Hovakimian (2006), as an indicator variable equal to one if the change in the book value of debt(long-term debt plus short-term debt) exceeds 5% of total assets. Change Firm is equal to one for firms reported as single-segment firms under SFAS 14 but revealed previously hidden information about their industry operations (diversification status) upon adoption of SFAS 131, and zero otherwise. Post SFAS 131 is a variable equal to one for the Post-adoption period, and zero otherwise. Regressions in Columns (1) and (2) include firm and year fixed effects. The coefficients estimate for Change Firm in Columns (1) and (2) are suppressed because of firm fixed effects. Regressions in Columns (3) and (4) are estimated using the logistic model and include Fama-French 48 industry and year fixed effects. Standard errors are clustered at the firm level (in brackets). ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variable definitions and sources of data are described in the Appendix.

	[1] Stock Illiquidity	[2] Net Financing	[3] Equity Issuance Dummy	[4] Debt Issuance Dummy
Change Firm × Post SFAS 131	-0.1343**	0.1045*	0.4547*	-0.2886
	(2.35)	(1.86)	(1.78)	(-1.19)
Change Firm			-0.0969	0.1468*
			(-1.09)	(1.83)
Post SFAS 131	-0.0017	-0.1865***	-0.5564***	0.0393
	(0.09)	(-6.10)	(-3.56)	(0.32)
Firm size	-0.1806***	-0.2477***	-0.2519***	0.0692***
	(12.62)	(-9.68)	(-11.76)	(4.15)
Tangibility	0.2366**	-1.5571***	-1.6920***	1.4720***
	(-2.53)	(-10.38)	(-7.45)	(9.05)
ROA	-0.2690***	0.4842***	-1.3878***	-1.1971***
	(6.82)	(8.62)	(-11.47)	(-12.00)
MTB	-0.0196***	0.0201***	0.0352***	-0.0734***
	(5.74)	(3.66)	(2.71)	(-4.54)
Cash Holding	0.2717***			
	(5.08)			
Leverage	-0.3607***			
	(-7.15)			
Number of Segments	-0.1473	-0.0158	-0.5177	0.4747
	(-1.37)	(-0.15)	(-1.10)	(1.05)
Intercept	-1.1559***	1.9787***	-0.6093	-2.0049***
	(-10.79)	(13.25)	(-0.56)	(-3.98)
N	12082	12174	11557	12163
R^2	0.1388	0.1248	0.1403	0.0632
Firm effects	Yes	Yes	No	No
Industry effects	No	No	Yes	Yes
Year effects	Yes	Yes	Yes	Yes

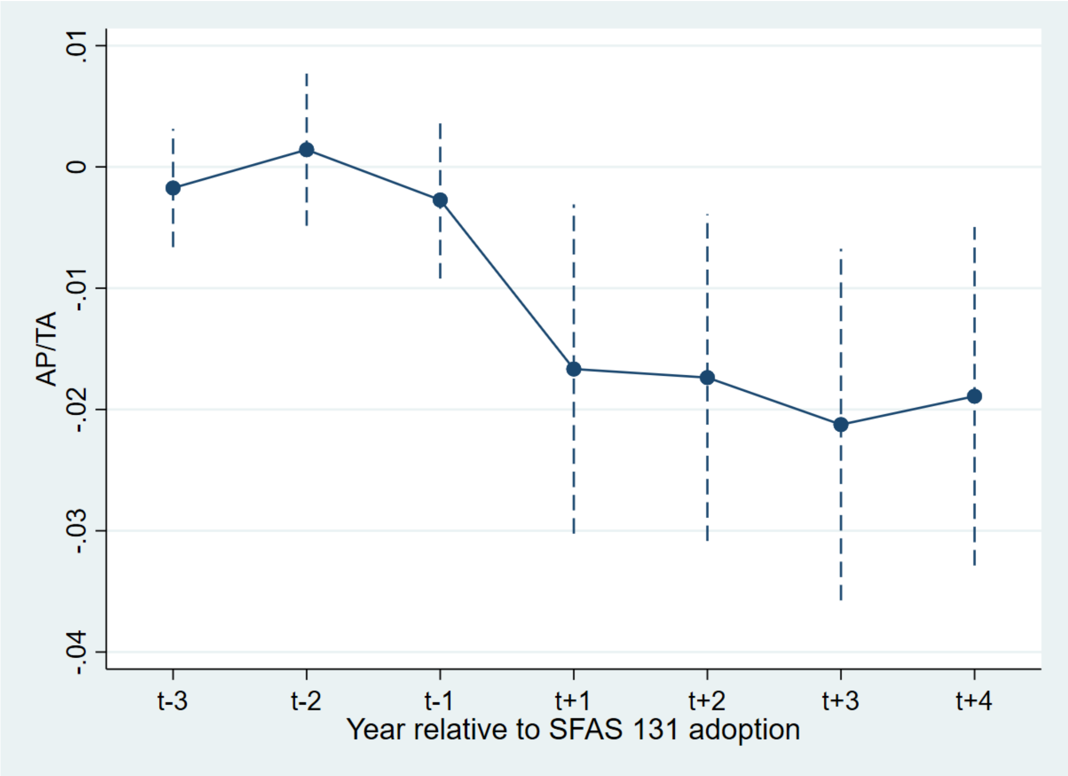

Figure 3.1. Parallel Pre-Treatment Trends

The figure shows the dynamic impact of SFAS 131 on the use of trade credit. Specifically, we plot the estimated coefficients and 95% confidence (in the dashed lines) for a set of leads and lags contained in the following specification: $AP/TA_{it} = \alpha + \sum_{t-3}^{t+4} \beta_t \times Change\ Firm_{it} + \theta X_{it} + \varepsilon_{it}$, where β_t represents the coefficient estimates of interactions between the Change Firm dummy and time indicators (with the fourth year before SFAS 131(t-4) as the reference year).

Appendix-Chapter 3

Table 3.A1. Variable Definitions

This table presents variable definitions and their source. All variables in italics are Compustat data items.

Variable	Definition	Data sources
Trade credit variables		
AP/TA	The ratio of accounts payable (*ap*) to total assets (*at*).	Compustat
AP/COGS	The ratio of accounts payable (*ap*) to cost of goods sold (*cogs*).	Compustat
AP/SALE	The ratio of accounts payable (*ap*) sales (*sale*).	Compustat
Firm-specific characteristics		
Firm size	The natural logarithm of sales (*sale*) in millions of U.S. dollars.	Compustat
Tangibility	The ratio of the total property, plant and equipment (*ppent*) to total assets (*at*).	Compustat
Cost of Goods Sold	The ratio of cost of goods sold (*cogs*) to total assets (*at*).	Compustat
Sales Growth	The percentage change in a firm's sales in the current year relative to the previous year (*sale* t - *sale* t-1)/*sale* t-1).	Compustat
Negative Growth	Sales growth times the negative growth dummy, which is equal to one if sales growth is negative and 0 otherwise.	Compustat
Positive Growth	Sales growth times the positive growth dummy, which is equal to one if sales growth is positive and 0 otherwise.	Compustat
R&D	The ratio of research and development (*xrd*) to total assets (*at*).	Compustat
ROA	The ratio of operating income before depreciation (*oibdp*) to total assets (*at*).	Compustat
MTB	The ratio market value of assets over book value of assets: [(*prcc_f* $*$ *csho*)- (*at*-*lt* + *txditc*) + *at*]/*at*.	Compustat
Cash Holding	The ratio of cash and short term investments (*che*) to total assets (*at*).	Compustat
Leverage	The ratio of total debt (*dltt*+*dlc*) to total assets (*at*).	Compustat
Market Share	The ratio of a firm's sales to total sales in its industry (Fama-French 48-industry definitions).	Compustat
Number of Segments	The number of unique 4-digit SIC business segments reported in Compustat Segment File by the firm in a given fiscal year.	Compustat Segment File
Other variables		
Ohlson	Ohlson (1980) O-score, calculated using his Table 4, defined as $\mathrm{O} = -1.32 - 0.407 \times \mathrm{SIZE} + 6.03 \times \mathrm{TLTA} - 1.43 \times \mathrm{WCTA} + 0.0757 \times \mathrm{CLCA} - 2.37 \times \mathrm{NITA} - 1.83 \times \mathrm{FULT} + 0.285 \times \mathrm{INTWO} - 1.72 \times \mathrm{OENEG} - 0.521 \times \mathrm{CHIN}$, where SIZE is the logarithm of the total assets (*at*) adjusted for inflation, as measured by the Gross National Product (GNP) Index, TLTA is the ratio of total liabilities (*lt*) to total assets (*at*), WCTA is the ratio of working capital (*act*-*lct*) to total assets (*at*), CLCA is the ratio of current liabilities (*lct*) to total assets (*at*),	Compustat

	NITA is the ratio of net income (*ni*) to total assets (*at*), FULT is the ratio of funds provided by operations (*pi*+*dp*) to total liabilities (*lt*), INTWO is a dummy variable that is equal to one if the firm has had a negative net income (*ni*) in the last two years, and zero otherwise, OENEG is a dummy variable that is equal to one if the firm's total liabilities (*lt*) exceed total assets (*at*). and zero otherwise, and CHIN is the change in the firm's net income, calculated as $\frac{ni_t - ni_{t-1}}{\lvert ni_t\rvert + \lvert ni_{t-1}\rvert}$. Ohlson O score probability of default is exp(Ohlson O-score) / 1 + exp(Ohlson O-score).	
Altman	Altman (1968) Z-score, calculated using his equation page 594 as $Z = 1.20 \times X1 + 1.40 \times X3 + 3.30 \times X3 + 0.60 \times X4 + 0.999 \times X5$, where X1 is the ratio of working capital (*act-lct*) to total assets (*at*), X2 is the ratio of retained earnings (*re*) to total assets (*at*), X3 is the ratio of earnings before interest (*oiadp*) to total assets (*at*), X4 is the ratio of the market value of equity (*prcc_f* ∗ *csho*) to total liabilities (*lt*), and X5 is the ratio of total sales (*sale*) to total assets (*at*).	Compustat
PIN	The Probability of informed trade, computed based on the Brown's calculation as $PIN = \frac{(mu \times alpha)}{mu \times alpha + 2 \times epsi}$, where mu is the trading intensity of informed traders, alpha is the probability of an information event, and epsi is the trading intensity of uninformed traders.	http://scholar.rhsmith.umd.edu/sbrown/pin-data
Idiosyncratic Risk	The standard deviation of residuals from Fama–French three-factor model.	Beta Suite by WRDS
Institutional Ownership	The percentage of shares outstanding owned by institutions.	Thomson Reuters Institutional Holdings
Blockholders	Indicator variable equal to one when institutional investors hold at least 5% of the firm's total outstanding shares.	Thomson Reuters Institutional Holdings
E-index	Entrenchment index constructed by Bebchuk et al.(2009). It is a function of six corporate governance provisions (e.g., staggered boards, limits to amend bylaws, limits to amend the charter, supermajority, poison pill, and golden parachutes) that restrict shareholder power over boards.	http://www.law.harvard.edu/faculty/bebchuk/data.shtml.
Big 4 Auditor	Indicator variable equal to one when a firm is audited by Big four audit firms include Ernst & Young, Deloitte, KPMG, and PricewaterhouseCoopers (Compustat item *au*).	Compustat
WW Index	Whited-Wu index calculated following Whited and Wu (2006) as –0.091 [(*ib* + *dp*)/*at*] – 0.062[dummy variable set equal to one if *dvc* + *dvp* is positive, and zero otherwise] + 0.021[*dltt*/*at*] – 0.044[log(*at*)] + 0.102[average industry sales growth] – 0.035[sales growth].	Compustat
HP Index	Hadlock and Pierce index calculated following Hadlock and Pierce (2010) as –0.737 Firm Size + 0.043 Firm Size^2 – 0.040 Firm Age, where Firm Age is the number of years the firm is listed on Compustat.	Compustat

Stock Illiquidity	Calculated following Amihud (2002) as the absolute value of daily stock return scaled by daily dollar volume, averaged over firm i's fiscal year t.	CRSP
Net financing	The sum of net equity measured as the difference between sales of common and preferred stock (*sstk*) and purchase of common and preferred stock (*prstkc*) plus net debt measured as change in long-term debt (*dltt*+*dd1*) scaled by lagged total assets(*at*) (Butler et al., 2011).	Compustat
Equity Issuance Dummy	indicator variable equal to one if the firm's gross equity issuance (i.e., sale of common and preferred stock (*sstk*)) is greater than or equal to 3% of its average year-begin and year-end market equity (*prcc_f* ∗ *csho*) (McKeon, 2015).	Compustat
Debt Issuance Dummy	Indicator variable equal to one if the change in the total debt (*dltt*+*dlc*) exceeds 5% of total assets (*at*) (Hovakimian, 2006).	Compustat

Table 3.A2. Variance inflation factors

This table presents the mean variance inflation factor (VIF) of all independent variables to quantify the severity of multicollinearity.

Variable	Mean VIF	VIF is estimated from
Change Firm	2.04	Column 2 of Table 3.3
Post SFAS 131	9.02	Column 2 of Table 3.3
Firm size	2.77	Column 2 of Table 3.3
Tangibility	2.62	Column 2 of Table 3.3
Cost of Goods Sold	1.58	Column 2 of Table 3.3
Negative Growth	1.40	Column 2 of Table 3.3
Positive Growth	1.25	Column 2 of Table 3.3
R&D	2.56	Column 2 of Table 3.3
ROA	2.23	Column 2 of Table 3.3
MTB	1.29	Column 2 of Table 3.3
Cash Holding	2.36	Column 2 of Table 3.3
Leverage	1.51	Column 2 of Table 3.3
Market Share	1.97	Column 2 of Table 3.3
Number of segments	8.38	Column 2 of Table 3.3

Table 3.A3. Excluding Firms: those Whose Historical Sales in Compustat Differ from Aggregated Segment Sales by More than 1%

This table presents results for the additional robustness checks when excluding firms whose annual sales differ from aggregated segment sales by more than 1%. The dependent variable is the ratio of accounts payable to total assets. Change Firm is an indicator variable equal to one for firms reported as single-segment firms under SFAS 14 but revealed previously hidden information about their industry operations (diversification status) upon adoption of SFAS 131, and zero otherwise. Post SFAS 131 is an indicator variable equal to one for the Post-adoption period, and zero otherwise. Regressions in Columns (1) and (2) include firm and year fixed effects. Coefficient estimates for Change Firm are suppressed because of firm fixed effects. Standard errors are clustered at the firm level (in brackets). ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variable definitions and sources of data are described in the Appendix.

	[1] AP/TA	[2] AP/TA
Change Firm × Post SFAS 131	-0.0052**	-0.0177**
	(-2.07)	(-2.31)
Post SFAS 131	0.0056***	0.0019
	(2.71)	(1.02)
Firm size		-0.0039**
		(-2.53)
Tangibility		-0.0258**
		(-2.51)
Cost of Goods Sold		0.0455***
		(12.62)
Negative Growth		0.0229***
		(3.49)
Positive Growth		0.0004
		(0.48)
R&D		0.0256*
		(1.87)
ROA		-0.0359***
		(-7.49)
MTB		0.0015***
		(4.10)
Cash Holding		-0.0746***
		(-11.05)
Leverage		-0.0032
		(-0.58)
Market Share		-0.0006
		(-0.02)
Number of Segments		0.0334**
		(2.26)
Intercept	0.0998***	0.0710***
	(63.35)	(5.06)
N	11669	11669
R^2	0.0073	0.2134
Firm effects	Yes	Yes
Year effects	Yes	Yes

Table 3.A4. Alternative Clustering

This table presents the results for the additional robustness checks using different clustering. Column (1) presents the results for when standard errors are clustered at the Fama-French 48 industries classification. Column (2) presents results when standard errors are adjusted for two-way clustering by the Fama-French 48 industries classification and year. Column (3) presents results when standard errors are adjusted for two-way clustering by firm and year. The dependent variable is the ratio of accounts payable to total assets. Change Firm is an indicator variable equal to one for firms reported as single-segment firms under SFAS 14 but revealed previously hidden information about their industry operations (diversification status) upon adoption of SFAS 131, and zero otherwise. Post SFAS 131 is an indicator variable equal to one for the Post-adoption period, and zero otherwise. Regressions in Columns (1)-(3) include firm and year fixed effects. Coefficient estimates for Change Firm are suppressed because of firm fixed effects. ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variable definitions and sources of data are described in the Appendix.

	[1] AP/TA	[2] AP/TA	[3] AP/TA
Change Firm × Post SFAS 131	-0.0178***	-0.0178***	-0.0178***
	(-3.48)	(-3.54)	(-3.91)
Post SFAS 131	0.0028*	0.0028	0.0028
	(1.96)	(1.62)	(1.50)
Firm size	-0.0028	-0.0028**	-0.0028**
	(-1.57)	(-2.09)	(-2.28)
Tangibility	-0.0254	-0.0254***	-0.0254***
	(-1.60)	(-2.62)	(-3.14)
Cost of Goods Sold	0.0436***	0.0436***	0.0436***
	(10.72)	(16.04)	(15.75)
Negative Growth	0.0246***	0.0246***	0.0246***
	(3.08)	(3.78)	(4.21)
Positive Growth	0.0002	0.0002	0.0002
	(0.18)	(0.21)	(0.22)
R&D	0.0273**	0.0273**	0.0273**
	(2.29)	(2.41)	(2.55)
ROA	-0.0365***	-0.0365***	-0.0365***
	(-7.40)	(-7.24)	(-8.26)
MTB	0.0016***	0.0016***	0.0016***
	(5.45)	(5.01)	(5.15)
Cash Holding	-0.0737***	-0.0737***	-0.0737***
	(-6.97)	(-11.71)	(-14.37)
Leverage	-0.0045	-0.0045	-0.0045
	(-0.60)	(-0.90)	(-1.03)
Market Share	-0.2567	-0.2567	-0.2567
	(-1.01)	(-1.21)	(-1.21)
Number of Segments	0.0312***	0.0312***	0.0312***
	(3.38)	(3.42)	(3.59)
Intercept	0.0648***	0.0648***	0.0648***
	(5.29)	(6.17)	(6.35)
N	12174	12174	12174
R^2	0.2095	0.2095	0.2095
Firm effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes

Chapter 4 Conclusion

This thesis empirically examines issues to advance our understanding of what drives corporate trade credit. We address two issues related to the use of trade credit as a source of financing, namely, financial distress and segment information disclosure. The two issues are closely related to corporate trade credit, but are inherently intertwined. First, in Chapter 2 of this thesis, we show that financially distressed firms increase their use of trade credit as a source of financing, because their ability to raise external financing is severely limited. This arises due to concerns relating to a possible default, in which traditional capital markets are less willing to provide additional financing. Given that traditional capital providers face high information asymmetry about creditworthiness when firms are distressed, they become reluctant to extend further financing. In such cases, suppliers have an advantage in providing liquidity to their distressed firms because they can better monitor and assess their customers' credit risk than traditional lenders and equity investors. Thus we hypothesise, and empirically observe a positive impact of financial distress on the use of trade credit. Second, in Chapter 3, we examine the effect of segment information disclosure which reduces information asymmetry about the firm's true underlying diversification and its co-insurance effect that lowers default risk (Lewellen, 1971). As a result, trade credit is expected to fall when more segment information is disclosed. Our results support this view, showing that exogenous changes in the firm's information environment caused by the mandatory adoption of segment disclosure (SFAS 131) improve the firm's access to sources of financing and lead to a decrease in the use of trade credit. These findings are consistent with the view that the reduction in the firm's information asymmetry allows the firm to substitute trade credit financing with other sources of financing (e.g., equity) that are informationally sensitive. Therefore, Chapter 3 complements Chapter 2 by providing additional evidence that segment information plays a crucial role in the firm's credit risk assessment and drives the use of trade credit.

We provide below a summary of the main findings of this thesis, recommendations and implications for practices, limitations, and directions for future research.

4.1 Summary and Key Findings

Chapter 2 studies whether financially distressed firms can rely on trade credit. Although previous studies (e.g., Molina and Preve,2012; Garcia-Appendini and Montoriol-Garriga, 2020) document an association between financial distress and the use of trade credit, their findings are somewhat mixed, casting some doubt on this relationship. Our study aims to reconcile the conflicting results of these studies by examining this relationship using more sophisticated measures of financial distress. There is an extensive literature (e.g., Hillegeist et al., 2004; Agarwal and Taffler, 2008) that argues that market-based measures of financial distress may outperform accounting-based measures, because such measures can reflect all of the information contained in accounting statements, as well as information that is not included in accounting statements. Thus, the relationship between financial distress and the use of trade credit could be more nuanced when we examine this link using both market-based and accounting-based measures of financial distress. Such analysis has not previously been undertaken, which may mean that important information about a firm's financial distress has not been considered in previous research.

Using data on U.S. public firms for the period 1976-2017, empirical findings of this chapter show that firms rely more on trade credit as a source of financing when they are in financial distress. In particular, using the Merton (1974) distance to default as a market-based measure of financial distress and the Altman (1968) Z score as an accounting-based measure, we find a positive and significant relationship between financial distress and the use of trade credit. These results remain highly robust to alternative measures of trade credit and alternative measures of financial distress. The robustness of the main findings is also confirmed when we use alternative model specifications, such as two-way clustering and Fama-MacBeth regressions.

We further establish the causality between financial distress and the use of trade credit. An important concern is that financial distress may be endogenously associated with the use of trade credit. For example, it could be that increasing the use of trade credit increases financial distress (i.e., reverse causality). Also, there may be some unobserved variables that affect both trade credit and financial distress (i.e., omitted variable bias). To the best of our knowledge, no study so far explicitly addresses the potential endogeneity concerns despite the importance of this issue if suitable conclusions are to be drawn. Thus, we address these endogeneity issues through several endogeneity tests. First, we use the propensity score matching approach to account for the observable differences between distressed and non-distressed firms. Second, we adopt a high-dimensional fixed-effects model to control for unobservable heterogeneity. Third, we conduct instrumental variable (IV) analysis to identify the impact of exogenous variation in financial distress on the use of trade credit. Fourth, we apply a difference-in-differences method, using the 2007-2008 financial crisis as an exogenous shock to financial distress, to establish a causal effect of financial distress on the use of trade credit. Finally, we conduct difference-in-difference-in-differences (DiDiD) estimation, using hurricane strikes as an exogenous shock to financial distress. Empirical evidence from these identification strategies suggests a positive causal effect of financial distress on the use of trade credit. This provides greater confidence in our results regarding the direction of causality between financial distress and the use of trade credit.

Furthermore, Chapter 2 performs two cross-sectional tests to better understand the impact of financial distress on the use of trade credit. The cross-sectional tests reveal that the positive effect of financial distress on trade credit is more pronounced among firms with more opaque information environments and those in regions characterised by low social trust. Overall, our findings support the view that suppliers are more willing to help their financially distressed customers because they have a better ability to assess the creditworthiness of their customers, monitor them and force repayment of the credit in the case of default. However, our further analysis shows that financially distressed firms cannot rely on trade credit when they are very risky or would affect their suppliers' value negatively. More specifically, we find the positive relationship between financial distress and the use of trade credit is weakened when firms are major customers to their suppliers. This finding is consistent with the argument that when suppliers have major customers facing financial distress, they may suffer from the negative spillover effect, with a resulting decrease in their valuation if they continue to help such customers (e.g., Hertzel et al., 2008; Kolay et al., 2016). As a result, suppliers may be less willing to offer trade credit to their distressed major customers. Moreover, we find an inverted-U relationship between financial distress and the use of trade credit: the use of trade credit increases with financial distress, but it decreases at very high distress levels.

Taken together, the findings of Chapter 2 contributes to the existing literature on trade credit by providing novel and intriguing evidence to the debates regarding the impact of financial distress on the use of trade credit. Using market-based and accounting-based measures of financial distress, we extend the work of Molina and Preve (2012) and Garcia-Appendini and Montoriol-Garriga (2020). This chapter expands upon the work of Molina and Preve (2012) by showing that when firms face financial distress, they will increase their use of trade credit; we also complement the findings of Garcia-Appendini and Montoriol-Garriga (2020) by highlighting that financially distressed firms cannot rely on trade credit when the level of financial distress is extremely high. Importantly, this chapter extends these previous papers by properly accounting for the endogeneity of financial distress to provide more precise estimates of the causal effect of financial distress and the use of trade credit. Finally, the findings of this chapter offer new insights into whether suppliers help their distressed customers because they have an implicit equity stake in their customers' business (Wilner, 2000; Cuñat, 2007). We show that suppliers tend to extend less trade credit to their major customers when customers are in financial distress. Our evidence does not support the argument that suppliers have the incentive to offer trade credit to their distressed major customers to maintain their business ties with these customers (e.g., Wilner, 2000). Instead, our findings highlight the potential negative spillover effect of major customers' financial distress on the supply chain, which could lead suppliers to stop the supply of goods on credit or offer less trade credit to their distressed major customers. (e.g., Hertzel et al., 2008; Jorion and Zhang, 2009). Our study provides new evidence that suppliers keep away from credit concentrations with their distressed major customers, but not with their non-distressed major customers.

Chapter 3 examines another important aspect affecting the firm's reliance on trade credit financing, namely, segment information disclosure. The literature on trade credit (e.g., Smith, 1987; Brennan et al., 1988; Biais and Gollier, 1997) argues that firms rely more on trade credit when they have limited access to traditional financing sources due to information asymmetry problems. Suppliers may have the incentive to extend trade credit to these firms because they have an informational advantage over traditional financial institutions in assessing their customers' credit risk (e.g., Biais and Gollier, 1997; Burkart and Ellingsen, 2004). There are a number of empirical studies in the literature that provide support for this argument by considering different sources of information that could affect the use of trade credit, such as analyst coverage (Chemmanur and Toscano, 2019), accruals quality (Chen et al., 2017), and the adoption of international financial reporting standards “IFRS” (Li et al., 2021). However, no study has yet examined whether segment information disclosure affects the use of trade credit. This source of information is value-relevant and informative to capital market participants because it plays an important role in firms’ credit risk assessment, and thus it will affect the use of trade credit.

This empirical chapter specifically uses the change in U.S. segment reporting rules from SFAS 14 to SFAS 131, in 1998/1999, as a quasi-natural experiment to investigate the effect of an exogenous change in the firm's information environment on a firm's use of trade credit. Using a sample of U.S. public firms from 1994 to 2002, we find that the adoption of SFAS 131 leads to a decrease in the use of trade credit. We undertake a number of robustness tests and show that our results hold when using an alternative control group sample, a matched sample, alternative model specifications, and different estimation windows, as well as alternative measures of trade credit. Furthermore, we show that the negative impact of the adoption of SFAS 131 is more important for treatment firms with high ex-ante default risk, a more opaque information environment, weak governance, and with non-Big 4 auditors.

The findings of Chapter 3 provide strong evidence that after the adoption of SFAS 131, firms reveal more complete information about their corporate diversification status, which helps capital market participants assess the firm's risk more effectively. Consequently, firms that have revealed new information about their corporate diversification status under SFAS 131 benefit from this regulatory change that improves their access to traditional sources of financing, which leads to a decrease in their reliance on trade credit. Our further analysis uncovers that the adoption of SFAS 131 lowers firms’ financial constraints and stock illiquidity, and increases equity issuance. These findings shed new light on how the reduction in the information asymmetry through the adoption of SFAS 131 improves the firm's access to sources of financing, which leads to firms substituting trade credit financing with other cheaper sources of financing that are more sensitive to information.

Overall, Chapter 3 makes two important contributions to the literature. First, the chapter adds to the growing literature on trade credit (e.g., Petersen and Rajan, 1997;

Giannetti et al., 2011; Nilsen, 2002; Love et al., 2007; Garcia-Appendini and Montoriol-Garriga, 2013; Abdulla et al., 2017; Chemmanur and Toscano, 2019; Chen et al., 2017; Shang, 2020; Li et al., 2021). While the effect of analyst coverage and financial reporting, as a source of information for the firm's capital providers, on the use of trade credit has been documented (e.g., Chemmanur and Toscano, 2019; Chen et al., 2017; Li et al., 2021), this chapter provides the first empirical evidence that segment information disclosure can drive the use of trade credit. Second, this chapter contributes to the existing literature on the adoption of SFAS 131. Several studies point to the beneficial role of this regulatory change on the firm's information environment (e.g., Herrmann and Thomas, 2000; Berger and Hann, 2003; Cho, 2015; Jayaraman and Wu, 2019; Franco et al., 2016). The findings of this chapter extend these studies by showing that the improved information environment after the adoption of SFAS 131 allows capital market participants to better assess the firm's credit risk, helping firms access traditional sources of financing rather than use the relatively more expensive trade credit.

4.2 Implications and Recommendations for Practice

Taken together, the two empirical chapters of this thesis improve our understanding of what drives the use of corporate trade credit. This has potential implications for capital market participants, managers, and regulators. The findings of Chapter 2 highlight that trade credit is a very important source of short-term financing for financially distressed firms. Such a finding is particularly beneficial for the managers of firms facing financial distress and seeking to find an alternative source of financing to make up for the lack of other conventional sources. At the same time, however, the findings of Chapter 2 suggest that managers should pay serious attention to a decrease in financial support from suppliers when their firms face a very high level of financial distress.

Moreover, Chapter 3 shows that segment information disclosure has a significant impact on the use of trade credit. The findings of Chapter 3 highlight the usefulness of segment information in evaluating firms' credit risk by various stakeholders and capital market participants. Also, the findings of Chapter 3 may increase the firm managers' awareness of the beneficial effect of segment information disclosure, which could affect the firm's financing choices and facilitate the firm's access to sources of financing. In addition, the significant effects of the adoption of SFAS 131 inform regulators about how the new standard has impacted firms' information environment and financial decisions.

4.3 Limitations

The main limitation of this thesis is that, while our trade credit measure has been widely used in the literature (e.g., Petersen and Rajan, 1997; Fisman and Love, 2003; Cuñat, 2007; Giannetti et al., 2011) and also our results are robust to alternative measures of trade credit, we are unable to examine trade credit contract terms to support several inferences in our thesis. For example, while we find in Chapter 2 that financially distressed firms use more trade credit, it remains unexplored whether financially distressed firms receive trade credit with high effective interest rates. The availability of the data on trade credit contract terms could enable us to provide, for example, more support in favour of non-financial motives for trade credit usage (e.g., price discrimination) that could drive our results. Prior studies on trade credit (e.g., Giannetti et al., 2011; Klapper et al., 2012) have investigated trade credit contract terms using data from the National Survey of Small Business Finances. It would be fruitful to examine trade credit contract terms of public firms, which can substantially enhance our understanding of trade credit financing.

4.4 Directions for Future Research

For academic researchers, the findings of the work undertaken in this thesis have some suggestions. First, we have assessed the impact of market-based and accounting-based measures of financial distress on the use of trade credit. Our study, therefore, opens up new opportunities for further research using different measures of financial distress to examine the impact of financial distress on various aspects of firm behaviour. Second, we encourage future researchers to establish the causal effects of financial distress using quasi-natural experimental settings. It is promising for future research to exploit potential exogenous events that increase financial distress to examine how such increases affect corporate financial and non-financial policies (e.g., corporate investment, corporate social responsibility). Furthermore, since our findings in Chapter 3 highlight that the adoption of SFAS 131 leads firms to substitute trade credit with other sources of financing, we encourage future researchers to further investigate the impact of the mandatory adoption of SFAS 131 on different types of private and public debt, such as credit lines, term loans, senior bonds, and subordinated bonds.

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