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STOCK RETURNS EVIDENCE

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ABSTRACT

Payment timeliness in trade credit transactions is a key metric suppliers use to monitor their buyers. However, firms are not required to disclose payment timeliness information. In theory, late payments could be either a positive or negative indicator of future performance. We find that late payment by buyers is negatively associated with future buyer financial performance and positively associated with subsequent default risk. This suggests that late payments are an indicator of inability to pay on time rather than an indicator that firms are delaying payments to fund profitable investments. The predictive power of payment timeliness for fundamentals is stronger for low liquidity and distressed firms. Finally, we find a significant association between payment timeliness and future stock returns, suggesting that investors do not fully incorporate payment timeliness information. Our evidence regarding the informativeness of payment timeliness is relevant for the ongoing regulatory debate on whether firms should disclose payment timeliness.

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1. INTRODUCTION

Trade credit is a major source of external financing for US firms. Roughly a quarter of corporate debt is trade credit, which is about three times the size of bank loans (Rajan and Zingales 1995; Barrot 2016; Ivashina, Iverson, and Smith 2016). Due to its size, and its more immediate implications for cash flows, buyers and suppliers devote substantial time and resources to managing trade credit compared to other sources of external financing (Long, Malitz, and Ravid 1993).

The importance of trade credit suggests that the trade credit repayment track records of buying firms may contain important information about firm value and future financial performance. However, it is not obvious on theoretical grounds whether timely payment of trade credit will be a positive or negative indicator about the firm's prospects. On the one hand, timely repayment may indicate that the borrower has little need for cash, i.e., few profitable investment opportunities. On the other hand, timely repayment may instead indicate that the firm's current activities are generating high cash flow.

We test here between these possibilities. Buyers report scant information about payment timeliness to suppliers, but the rise of alternative data providers has led to new types of disclosure by suppliers that are available at high cost. Specifically, aggregators collect information on account receivables from anonymous suppliers on web platforms for the purpose of monitoring buyers. We use this new proprietary data source of disclosures by suppliers to measure the percentage of trade credit payments that are past due and examine whether it is informative about future firm financial performance.

Regulators around the world have recognized the importance of payment practices in trade credit and are accordingly considering or have recently mandated more disclosure in this area. For example, Section 3 of the Small Business, Enterprise and Employment Act 2015 which became effective on April 6, 2017, requires large UK firms to self-report their payment practices including the percentage of late payments to suppliers. This requirement is meant to increase transparency of payment practices and it arose due to concerns that small- and medium-sized suppliers were suffering from cash flow problems due to late payments by buyers.[1] In the U.S. and abroad, the Financial Accounting Standards Board (FASB)[2] and the International Accounting Standards Board (IASB)[3] have made proposals (discussed below) related to factoring transactions which might require greater disclosure of information about payment timeliness.

A firm's failure to pay on time could result in contractual penalties (Fabbri and Klapper 2016). The firm also risks losing access to trade credit from that supplier in the future and potentially risks its ability to trade with that supplier at all (Smith 1987; Petersen and Rajan 1994, 1997). If late payments are a sign of a firm's inability to make timely payments, then late payments should be associated with poor subsequent performance and an increased default risk.

However, late payment by buyers could be a positive indicator of a firm's prospects. A common cash management policy involves strategically delaying payments to suppliers to free up cash to be used in alternative short-term investments (Emery 1984).[4] Similarly, customers with greater bargaining power can often delay payments with impunity (Murfin and Njoroge 2012). Furthermore, firms may not wish to harm trade credit relationships given alternative

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[1] See the UK report on "Duty to report on payment practices and performance" for further discussion of the justification for such policies (https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/574312/duty-to-report-on-payment-practices-and-performance-government-response.pdf).

[2] https://www.fasb.org/page/getarticle?uid=fasb_Media_Advisory_12-20-21_Body_0228221200&isNewsPage=true.

[3] https://www.ifrs.org/projects/completed-projects/2020/supply-chain-financing-arrangements-reverse-factoring/.

[4] https://www.wsj.com/articles/delaying-payments-to-suppliers-help-companies-unlock-cash-1530178201.

forms of financing are costly and involve additional contracting costs (Fisman and Love 2003; Li, Ng and Saffar 2021). If buyers primarily delay payments to suppliers to take advantage of investment opportunities or greater bargaining power, then late payments should be associated with positive firm performance and low default risk in the future.

In summary, there are two hypotheses regarding the relationship between a firm's late payments and its subsequent performance and default risk focusing on when firms violate these contract terms and for what cash management purposes. To test these two hypotheses, we employ a proprietary dataset of trade credit offerings between suppliers and buyers. These data are richer than typical payables disclosures and they include monthly records of accounts receivable for suppliers selling to publicly traded companies in the US. We observe the proportion of trade credit offered that is paid on time versus delinquent or past due, information that is not available in typical buyers' disclosures. We utilize these accounts receivable files, shared by anonymous supplying firms, to construct accounts payable for 4,176 distinct public firms that comprise 122,098 firm–quarters for the years 2002–2017. In our data, an average buyer obtains \$6.65 million trade credit from all suppliers each month and on average, 27% of this trade credit is past due.

We begin our analysis by examining whether late payments contain information about future firm performance. Our primary measure of firm performance is return on assets (ROA) in the next quarter. Our variable of interest is the percentage of total trade credit dollars that are past due (late payments). We find that late payments are negatively correlated with future ROA, suggesting that late payments are a sign of a firm's inability to make timely payments rather than positive alternative uses for that capital. To better understand the relationship between payment timeliness and future financial performance, we study the next quarter's sales growth and find that late payments are also negatively correlated with this measure. This indicates that late payments are not only associated with lower future profitability, but also with lower future growth.

We conduct three robustness tests on the association between late payments and future ROA. First, we control for firm fixed effects to examine the effect of within-firm variation of late payments. Second, we exclude from our sample the 2007-2009 financial crisis period, during which the relationship between trade credit and firm performance could be intensified by the contraction of bank credit. Third, we employ the entropy-balancing matched sample method to control for multiple moments of the covariate distribution. The empirical result of a negative association between late payments and future ROA is robust to these different specifications.

Next, we conduct cross-sectional analysis to provide further evidence as to whether late payments are an indicator of the firm's inability to pay on time rather than positive alternative uses for that capital. First, we examine whether the association between late payments and future performance varies with buyers' current liquidity level and find that it is more negative for buyers that have lower cash on hand and lower operating cash flows. This suggests that trade credit delinquency signaling poor future performance is driven by a lack of liquidity. Second, we examine the effect of buyers' long-term solvency and find that late payments are more negatively correlated with future performance for highly leveraged and financially distressed firms. This is consistent with late payments signaling more severe performance deterioration when buyers have already exhausted other sources of financing.

Trade creditors experience considerable losses when their customers undergo bankruptcy (Jorion and Zhang 2009).[5] In many cases, the failure of a buyer will spill over to its creditors. This

[5] Sautner and Vladimirov (2018) find that strict ex post enforcement of debt contracts in bankruptcy proceedings improves recovery rates, which indirectly benefits financially distressed firms by improving their access to trade credit.

spillover constitutes a nontrivial portion of aggregate bankruptcy (Jacobson and von Schedvin 2015). This makes understanding leading indicators of buyer performance even more important not only to investors but also to the supply chain. We examine whether late payments are related to more dire outcomes, specifically whether they are indicative of a debtor firm's default risk.

We use three measures to estimate default risk over the next six months: the change in the firm's credit rating; the probability that the firm files for bankruptcy; and the probability of the firm's auditor issuing a going concern opinion. Consistent with expectations, we find that the percentage of late payments is positively associated with default risk. For example, moving from the bottom to the top quintile of past-due percentage of trade credit is associated with an increase in the log odds of bankruptcy by 0.73 (odds increased by 107%). The existence of a substantial relationship between this trade credit information and the buyer's default risk further demonstrates the information content in late payments.

While we show that late payments are informative about future performance and default risk, the argument for increasing disclosures about the status of trade credit payments should also depend upon whether this information is already incorporated in stock prices. A firm's payment timeliness is made available to potential trade partners by subscription data vendors, but this information is not publicly available to the typical investor. Nonetheless, since some parties do possess this information, it is possible that the stock market incorporates it, weakening the justification for requiring increased disclosures. We examine whether the information content in late payments predicts future abnormal returns for the buyer. Consistent with this information not already being fully incorporated in public markets, we find that the percentage of past due trade credit is negatively correlated with returns around the next-quarter earnings announcement.

Moreover, a portfolio that buys stocks with low past-due percentage and sells stocks with high past-due percentage earns significant positive risk-adjusted returns.

Our study contributes new insights to the disclosure literature (for a review, see Leuz and Wysocki 2016).[6] In recent years, regulators around the world have identified the importance of payment practices in trade credit, and are considering mandating or have already mandated its disclosure. Our evidence provides insight about whether aggregated disclosure by suppliers about their buyers could constitute material disclosure if made public to markets. If an investor were to use days payable calculations to find that a firm is making later payments, this could be a positive indicator that the firm is receiving more relaxed payment terms (e.g., payment is due 90 days after invoice as opposed to payment is due in 60 days after invoice). However, we show that once payments are past due, higher days payable can instead be a negative indicator. Current disclosures do not make this non-monotonicity transparent to investors.

Furthermore, the FASB and the IASB have recently proposed standards related to reverse factoring.[7] In factoring transactions, a third party (typically a bank or other financial institution) pays off the company's suppliers early and the company pays that third party at a later date.[8] Unlike in a regular factoring transaction, in reverse factoring the buyer initiates the transaction with the third party, meaning the supplier does not know if the buyer is past due with that third party. While this loss of private information may not impact immediate transactions financed by the third party, future business could be disrupted, harming the seller.[9] To shed light on payment

[6] New technologies have changed the dissemination (e.g., Blankespoor, Miller, and White 2014) and acquisition (e.g., Drake, Roulstone, and Thornock 2012) of firm information. Moreover, recent research shows that disclosures made by employees of the firm are leading indicators of firm performance (e.g., Huang, Li, and Markov 2020; Li, Lourie, Nekrasov and Shevlin 2021). We extend this literature by examining information known by a third-party stakeholder group outside the firm.

[7] https://www.fasb.org/page/getarticle?uid=fasb_Media_Advisory_12-20-21_Body_0228221200&isNewsPage=true.

[8] https://www.fasb.org/jsp/FASB/FASBContent_C/ProjectUpdateExpandPage&cid=1176175475663.

[9] See also the nascent literature that studies whether suppliers have private information about buyers (Ivashina and Iverson 2018; Costello, Down, and Mehta 2020).

timeliness, IASB proposed a disclosure of payment terms for all types of transactions. In a comment letter, the International Trade and Forfaiting Association opposed this disclosure since they believe there is no value in such granular details.[10] Since buyer payment timeliness is obscured by reverse factoring arrangements, our finding that timeliness is a leading indicator of performance and default risk of the buyer provides insight into this standard setting debate. In fact, the FASB recently invited the author team to present the study to the FASB's project team developing the new accounting standard on reverse factoring.[11]

We also contribute to research on the relationship between trade credit information and firm performance. Most prior work examines the return predictability of economically linked firms.[12] The research suggests that supplier stock prices do react to customer returns, but not in a timely manner (Olsen and Dietrich 1985; Cohen and Frazzini 2008; Menzly and Ozbas 2010; Pandit, Wasley, and Zach 2011; Madsen 2017). Suppliers suffer negative and significant stock price effects when their buyers file for bankruptcy (Hertzel, Officer, and Rodgers 2008). In addition, customers are gravely affected when suppliers experience natural disasters (Barrot and Sauvagnat 2016).[13] However, there is little evidence on whether late payments by customers are associated with their future financial performance.

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[10] https://www.gtreview.com/news/global/global-supply-chain-finance-disclosure-rules-divides-industry-investors/.

[11] See Appendix A for the invitation from the FASB.

[12] Our paper also contributes to the growing literature documenting that equity markets are slow to account for non-public information understood by creditors. In a recent paper, Addoum and Murfin (2019) show that when information about a firm is understood in private loan markets and reflected in publicly posted loan prices, this information is only later reflected in equity prices.

[13] Albuquerque, Ramadorai, and Watugala (2015) show that cross-country trade credit linkages are related to individual firm returns. Goto, Xiao, and Xu (2015) find that trade credit intensity is related to subsequent market returns. We extend the results of their paper by investigating returns surrounding fundamentals-based informational events (e.g., earnings announcements), investigating volatility separately, and incorporating richer data that can also speak to the amount of past-due trade credit that also has information content. For example, we control for accounts payable (their explanatory variable of interest) in all our regressions.

2. DATA

2.1 Sample selection and distribution

We obtain monthly records of trade credit from a proprietary data vendor. This data vendor provides suppliers with a platform to manage their buyers' risk profiles. Suppliers share their accounts receivable files with this data vendor, from which the aging schedule for each buyer can be extracted. The data vendor provides the identification information of the buyer, but anonymizes suppliers to protect its clients' identities. We obtain buyers' financial data and Standard & Poor's (S&P) credit ratings from the Compustat North America file, stock returns from CRSP, analyst forecasts from I/B/E/S, and auditor opinions from Audit Analytics. In addition, we identify firms that have filed for bankruptcy from 8-K filings and CRSP delisting codes.

Table 1 Panel A presents details of the sample selection. The initial sample from the data vendor includes monthly records of 32,706 distinct buyers (2,332,947 buyer–months) from July 2002 to December 2017. We restrict the sample to public companies listed on NYSE, AMEX, and NASDAQ and exclude financial firms. That leaves 5,045 distinct buyers (436,766 buyer-months) with monthly trade credit information. To merge this information with quarterly financial data, we convert raw monthly trade credit records to quarterly trade credit data by averaging trade credit over the three months of a fiscal quarter. Observations that lack valid financial data are removed from the sample. The final sample contains 122,098 quarterly trade credit records for 4,176 distinct buyers from July 2022 to December 2017.

Table 1 Panel B presents the distribution of sample observations by year. The dataset covers 880 distinct buyers in 2002. The number of distinct buyers increased steadily over the next 15 years to around 2,400 buyers each year. This growth indicates that the data vendor has incorporated accounts receivable files from more suppliers and expanded coverage to more buyers over time.

Table 1 Panel C describes the sample distribution of the buyer's industry and compares it to the distribution of the stock universe. We define 12 industries using the Fama–French classification.[14] Our sample covers about half (4,176/8,745 = 47.8%) of the firms listed on NYSE, AMEX, and NASDAQ. After excluding the Finance industry, our sample has a similar distribution across industries as the universe of stocks, with slightly more firms from Manufacturing (11.6% versus 9.9%) and Wholesale, Retail, and Some Services (11.9% versus 10.1%) and fewer firms from Business Equipment (24.4% versus 26.3%) and Other (12.8% versus 15.7%).

2.2 Variable measurement

For each buyer, we aggregate trade credit from all suppliers in each month and then calculate the average amount of trade credit over the three months of a fiscal quarter. The amount of total trade credit (*TradeCredit*) can be split into the amount that is current (*OnTime*) and the amount that is delinquent (*PastDue*). We also deflate trade credit by the buyer's accounts payable balance at the current fiscal quarter end (*TradeCredit/AP*) to gauge the coverage of our dataset. From the balances in the aging buckets, we calculate the percentage of trade credit dollars that is past due in each month. We then obtain the quarterly average past due percentage (*PastDue%*) by value-weighting the monthly percentages by the amount of total trade credit in each month.

To measure accounting performance, we calculate buyers' return on assets (*ROA*) and seasonal changes in sales (Δ*Sales*) in each quarter. We use three measures to estimate a buyer's default risk over the next six months: (a) the signed change in its S&P credit rating

[14] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

(*CreditRating_chg*), (b) the probability that the buyer will file for bankruptcy (*Bankruptcy*), and (c) the probability that the buyer's auditor will issue a going concern opinion (*GoingConcern_next*). To investigate the relationship between trade credit and future stock returns, we calculate cumulative market-adjusted abnormal returns around the earnings announcements of the next fiscal quarter (*CAR[-1, +1]_q+1* and *CAR[-3, +3]_q+1*). Definitions of all variables are provided in Appendix B.

Table 2 Panel A reports summary statistics of trade credit variables for all buyer–quarters. On average, each buyer receives $6.65 million in trade credit each month and 27% of this trade credit is past due (*PastDue%*). Compared to the magnitude of accounts payable for the same quarter, the average ratio of trade credit to the buyer's accounts payable (*TradeCredit/AP*) is 2.24%, suggesting limited coverage by our dataset. Thus, we focus on the percentage of trade credit that is past due, rather than the size of trade credit in this study.

Table 2 Panel B reports summary statistics of buyers' financial condition, default risk and stock return variables. Our sample is tilted toward larger firms. The sample mean (median) total assets (*AT*) is $5.373 billion ($855 million), which is larger than the mean (median) total assets of $3.834 billion ($441 million) in the stock universe (untabulated). The mean (median) quarterly return on assets (*ROA*) is 0.20% (1.03%) and the mean (median) quarterly sales change (Δ*Sales*) is 1.35% (1.19%). Turning to default risk, the median most recent S&P credit rating code (*CreditRating_recent*) is -13, which corresponds to a letter rating of BB+.[15] This means that half of the sample observations receive non-investment grade ratings. Around 0.10% of the sample

[15] See Appendix C for details about how the numeric credit rating codes are matched to letter ratings.

firms file for bankruptcy in the next six months (*Bankruptcy*), and 0.80% receive a going concern opinion from auditors in the next six months (*GoingConcern_next*).

3. RESEARCH DESIGN AND RESULTS

3.1 Late payments and future performance

Delaying payment to suppliers is met with significant costs, due to contractual penalties that may be incurred (Fabbri and Klapper 2016) and the risk posed to the ability to trade with that supplier in the future (Smith 1987; Petersen and Rajan 1994, 1997). On theoretical grounds, firms therefore should be unlikely to delay payments unless there is a reason to do so. What is unclear ex ante is whether the reason is a negative signal about the firm's prospects (e.g., liquidity problems) or a positive signal about the firm's prospects (e.g., profitable investment opportunities).

In this section, we test between these competing hypotheses about the relation of delayed payment and future performance. We formally state the competing hypotheses here.

H1: Late payments are negatively correlated with buyers' future accounting performance.

Delinquency could be the result of liquidity problems at the buyer firm. When cash becomes tight, managers may decide to forgo making timely payments to service other debt, balance payrolls, or make payments to other suppliers. If liquidity issues are an important factor in late payments and are also indicative of poor operations, or if the costs to delaying payments are too great, then late payments should be associated with poor subsequent performance and an increased default risk.

On the other hand, the decision to delay payments to suppliers may indicate positive prospects for a firm. Delaying payments to suppliers could free up cash to be used in alternative short-term investments. Moreover, firms that delay payments are shown to possess significant bargaining power (Murfin and Njoroge 2012), a positive indicator of future performance. Firms may avoid delaying payments unless they have profitable opportunities due to the significant costs of finding alternative sources of financing (Fisman and Love 2003; Li, Ng and Saffar 2021). If buyers delay payments to suppliers to fund profitable investment opportunities or because they have greater bargaining power, we will instead expect late payments to be associated with positive firm performance and low default risk in the future. Our competing hypothesis is stated here.

H2: Late payments are positively correlated with buyers' future accounting performance.

To investigate whether payment timeliness for trade credit contains valuable private information about buyers' future fundamentals, we first examine the relation between delinquent trade credit and buyers' future accounting performance. Specifically, we focus on the proportion of total trade credit that is past due (*PastDue%*). We test the association between late payments and future accounting performance in a quarterly sample using the following equation:

$$Y_{i,\,q+1} = \beta_0 + \beta_1\, r\_PastDue\%_{i,q} + \beta_2\, Y_{i,q} + \beta_3\, Controls_{i,q} + \beta_4\, FEs_{i.q} + \delta_{i,q}, \qquad (1)$$

where Y_{q+1} is one of the two accounting performance variables of quarter $q + 1$: a profitability measure—return on assets (*ROA*), and a growth measure—seasonal changes in sales ($\Delta Sales$). The key explanatory variable, *r_PastDue%*, is the quintile rank of *PastDue%* in quarter q.[16, 17] We predict that $\beta_1 < 0$ if trade credit delinquency indicates liquidity problems instead of bargain power. To examine whether trade credit contains private information beyond what is disclosed in financial statements, we control for the corresponding Y and a set of control variables (*Controls*) measured

[16] For each quarter, we sort all firms into five groups based on *PastDue%* and then scale the ranks to [0, 1], which gives $r\_PastDue\% \in \{0, 0.25, 0.5, 0.75, 1\}$.
[17] In untabulated tests, we find that our results on firm fundamentals are robust to sorting by deciles or using winsorized continuous versions of our independent variables.

at the end of quarter *q*. These *Controls* include: (a) the natural logarithm of buyers' market value of equity (*SIZE*) and book-to-market ratios (*B/M*) to control for performance that may be related to market capitalization, (b) accounts payable deflated by total assets (*AP/AT*) to control for dependence on trade credit in general, (c) growth in total assets (*GrowAT*), (d) cash and cash equivalents scaled by total assets (*Cash/AT*), (e) cash flows from operating activities deflated by the average current liabilities (*CFO/CL*) to control for life cycle and liquidity effects, (f) total liabilities divided by total assets (*Leverage*), (g) an ordinal variable of default risk based on the Altman Z-score (*Distress*), and (h) industry-adjusted abnormal current accruals (*AdjAccrual*). We add industry and year–quarter fixed effects to each equation to control for industry characteristics and time trends in accounting performance.

Table 3 presents the results from the estimation of Equation (1) in a sample of 122,098 firm–quarters.[18] Consistent with our prediction, *r_PastDue%* is negatively correlated with both *ROA* and Δ*Sales* in the next quarter after controlling for the lags of each variable and known accounting predictors of future performance. These results suggest that trade credit provides information about future accounting performance beyond what is publicly disclosed in financial statements. Failure to pay trade credit on time signals liquidity problems rather than alternative positive investment opportunities. This information is likely to be known only by the supplier and buyer.

3.2 Late payments and default risk

Next, we examine whether trade credit is informative about buyers' default risk. We test whether the percentage of past-due trade credit (*PastDue%*) is a negative indicator, indicating

[18] The coefficients of *r_PastDue%* are expressed as a percentage to show them concisely.

increased liquidity problems and therefore a higher future default risk, or a positive indicator, indicating the firm has profitable investment opportunities and therefore a lower future default risk.

To test these predictions, we examine three measures of default risk over the next six months: (a) the signed change in a firm's S&P credit rating (*CreditRating_chg*), with an increase (decrease) representing a credit rating upgrade (downgrade); (b) whether a firm will file for bankruptcy (*Bankruptcy*); and (c) whether a firm's auditor will issue a going concern opinion (*GoingConcern_next*).[19] We test the relation between late trade credit payments and future default risk using the following equation:

$$Y_{i,\,q+6mon} = \beta_0 + \beta_1\, r\_PastDue\%_{i,q} + \beta_2\, Y_{i,\,recent} + \beta_3\, Controls_{i,q} + \beta_4\, FEs_{i.q} + \delta_{i,q}, \qquad (2)$$

where Y_{q+6mon} is one of the three default risk variables (*CreditRating_chg*, *Bankruptcy*, and *GoingConcern_next*) measured within six months after the end of quarter q. The variable of interest is the quintile rank of *PastDue%* in quarter q.

When Y is the change in the future credit rating, we predict Y will have a negative association with *PastDue%* ($\beta_1 < 0$). When Y is the probability of future bankruptcy or receiving a going concern opinion, we predict Y will have a positive association with *PastDue%* ($\beta_1 > 0$). Except for *Bankruptcy*, we control for the most recent Y before the end of quarter q (*CreditRating_recent* or *GoingConcern_recent*). To test the probability of receiving a going concern opinion, we also control for whether the firm's auditor is a Big Four auditor (*Big4*). The general control variables (*Controls*) and fixed effects are the same as those in Equation (1).

[19] Here we do not use Altman's Z-score as a measure of default risk, because Altman's Z-score is computed based on historical financial statement numbers and has already been included as control in all regressions. Instead, we use external realized events as the outcome variables.

Table 4 presents the results from estimating Equation (2) for each of the three default risk measures. Column (1) is estimated using the ordered logit model, because the change in credit rating is an ordinal variable that could include multiple categories. Columns (2) and (3) are estimated using the logit model because the dependent variables are binary variables.[20] Consistent with our predictions, we find that *PastDue%* is associated with lower future credit ratings and a greater likelihood to file for bankruptcy or receive a going concern qualification over the next six months. These effects are economically sizable: when moving from the bottom to the top quintile of *PastDue%*, the log odds of receiving a higher credit rating decrease by 0.26 (odds decreased by 23%), the log odds of bankruptcy increase by 0.73 (odds increased by 107%), and the log odds of receiving a going concern qualification increase by 0.42 (odds increased by 52%).[21] These findings suggest that failure to pay trade credit on time is an economically meaningful predictor of higher future default risk.

3.3 Late payments and stock returns

Given our evidence that delinquent trade credit is negatively associated with buyers' future accounting performance and positively associated with default risk, we next ask whether such information is known and incorporated in a timely way by the stock market. If existing public disclosures suffice and the information content of late payments is already incorporated by the stock market, late payments will not predict future stock returns. On the other hand, if trade credit delinquency is a private signal only observable by the suppliers and provides incremental information beyond all public disclosures, late trade credit payments will be negatively associated

[20] Our results are robust under alternative binary dependent variable models such as probit. Sample sizes are reduced due to the omission of observations when a fixed effect perfectly predicts failure or success.
[21] The relative percentage change in odds ratio is calculated by subtracting one from the exponential of the change in log odds. In other words, $Relative\%Change = e^{\Delta log\ odds} - 1$.

with future stock returns. Thus, we test the relation between late payments and buyers' future abnormal stock returns using two approaches.

First, we employ a portfolio approach to examine the return predictability of late payments. At the end of every month *t*, we sort all buyers' stocks into five portfolios based on *PastDue%*. The top portfolio contains stocks with the highest *PastDue%* and the bottom portfolio contains stocks with the lowest *PastDue%*. We then track stock performance over the following month and value weight stock returns within each portfolio.[22] For each month, we construct a long–short portfolio that buys the bottom *PastDue%* portfolio and short-sells the top *PastDue%* portfolio, and compute monthly returns from this zero-cost hedging portfolio (*Ret_L-H*). Portfolios are rebalanced every calendar month. To control for variation in exposure to systematic risk factors, we compute alphas from a time-series regression of portfolio returns on monthly factor returns based on the Fama-French (1993) 3-factor model and Carhart (1997) 4-factor model.[23] The alphas represent average monthly risk-adjusted abnormal returns earned by each portfolio. Given our prior evidence that late payments are linked to worse future performance and higher default risk, we predict positive alphas from the long-short portfolio.

Table 5 Panel A reports estimated alphas and factor loadings in the monthly sample of buyers. Consistent with our prediction, alphas under both asset pricing models are positive and statistically different from zero at the 1% level. Under the 3-factor (4-factor) model, the long-short portfolio that buys stocks with low *PastDue%* and sells stocks with high *PastDue%* earns risk-adjusted abnormal returns of 0.44% (0.43%) per month, or 5.34% (5.12%) annually.

[22] For value weighting, weight is the stock's market value of equity at the end of month *t*. Results are qualitatively similar if returns are equally–weighted (untabulated).
[23] Factor returns are obtained from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Second, we investigate whether late payments predict abnormal returns around future earnings announcements, when the information embedded in late payments is realized into earnings. We estimate the following equation in the quarterly sample of buyers:

$$Y_{i,\,q+1} = \beta_0 + \beta_1\, r\_PastDue\%_{i,q} + \beta_2\, EarnSurp_{i,\,q} + \beta_3\, Controls_{i,q} + \beta_4\, FEs_{i.q} + \delta_{i,q}, \qquad (3)$$

where Y_{q+1} is the cumulative market-adjusted abnormal returns in either the [-1, +1] window or the [-3, +3] window around the earnings announcement of quarter *q+1* (*CAR[-1, +1]_q+1* or *CAR[-3, +3]_q+1*). The variable of interest is the quintile rank of past-due proportion of trade credit in quarter *q* (*r_PastDue%*). In addition to *Controls* and fixed effects, which are the same as those in Equations (1) and (2), we control for the buyer's earnings surprise of quarter *q* (*EarnSurp*).

Table 5 Panel B presents the results from estimating Equation (3) in the quarterly sample. Consistent with our predictions, *r_PastDue%* is associated with lower abnormal returns around the next-quarter earnings announcements. Specifically, when *PastDue%* changes from the lowest quintile to the highest quintile, buyers' market-adjusted abnormal returns over the window [-1, +1] decrease by 0.235%. Taken together, results from Panel A and Panel B suggest that the information content of late payments has not been fully incorporated into stock prices and is largely private information of suppliers.

3.4 Cross-sectional analyses of late payments and profitability

Our results so far suggest that firms delay late payments because of liquidity problems rather than having profitable alternative uses for the funds. To further test between our hypotheses, we conduct subsample analyses based on buyers' current liquidity and solvency risks. We expect the negative association with future performance to be stronger for less-liquid and less-solvent buyers, because those buyers will have greater difficulty to repay delinquent trade credit, thus limiting their access to inventory and low-cost finance from trade partners in the future.

Table 6 presents the results of cross-sectional analyses. Every quarter, we partition the sample at the median by the buyer's current-quarter liquidity risk or solvency risk. Equation (1) is estimated in each subsample with *Y = ROA_q+1*. For conciseness, only coefficients of *r_PastDue%* are tabulated. The difference in coefficients of *r_PastDue%* across subsamples is tested by seemingly unrelated regressions (*SUR*).

Panel A reports analyses for short-term liquidity risk. We partition the sample by two inverse measures of liquidity risk: cash deflated by current liabilities (*Cash/CL*) and cash flow from operations deflated by current liabilities (*CFO/CL*). We find that the coefficients of *r_PastDue%* are more negative in low *Cash/CL* and low *CFO/CL* subsamples, consistent with the idea that trade credit delinquency driven by lack of liquidity is a stronger indicator of poor future performance. Panel B reports analyses for long-term solvency risk based on two measures: total liabilities divided by total assets (*Leverage*) and an ordinal variable of default risk based on the Altman Z-score (*Distress*). We find that the coefficients of *r_PastDue%* are more negative in high *Leverage* and high *Distress* subsamples, suggesting that when buyers have already exhausted other sources of finance, late payments signal more severe performance deterioration. Taken together, these findings corroborate the conclusion that late payments are an indicator of the inability to pay on time (Hypothesis 1), rather than an indicator of positive alternative uses for that capital (Hypothesis 2).

3.5 Robustness tests of late payments and profitability

It is possible that the negative correlation between late trade credit payments and future profitability is driven by uncontrolled confounding factors. To examine this possibility, we perform three sets of robustness tests.

First, we add firm fixed effects to our main specification to control for unobservable firm characteristics. Table 7 Column (1) reports the estimation results of estimating Equation (1), adding firm fixed effects. The past due percentage (*r_PastDue%*) is negatively associated with future return on assets, which suggests that late payments predict within-firm variation in performance.

Second, we test whether these findings are robust to exclusion of the 2007-2009 financial crisis. Trade credit plays an important role during times of monetary tightening (Meltzer 1960; Choi and Kim 2005; Garcia-Appendini and Montoriol-Garriga 2013). Prior studies find that negative shocks to bank financing during a financial crisis affect both supply and demand of trade credit (Garcia-Appendini and Montoriol-Garriga 2013; Costello 2020). Under contraction of bank credit, the dynamics between trade credit and firm performance can be intensified and different from non-crisis periods. Therefore, we test whether our findings are robust after excluding the peak years of the financial crisis (2007-2009). Table 7 Column (2) reports the estimation results of Equation (1) after removing all observations during 2007–2009. *r_PastDue%* is still negatively associated with future return on assets during the non-crisis period, albeit with a slightly smaller magnitude (-0.286 vs. -0.292).

Third, we employ the entropy balancing approach to mitigate concerns over higher moments of the control sample. Entropy balancing is a multivariate matching procedure that allows users to reweight a dataset to minimize differences in control variables between the treatment and control groups. It is more effective than simple matching or propensity-score matching, because it can achieve balance in multiple moments of the covariate distribution and relies on less restrictive assumptions (Hainmueller 2012). We create a matched sample by matching the treatment group (firms with above-median *PastDue%* each quarter) and the control group (firms with below-median *PastDue%* each quarter) on the first three moments of covariate distribution (mean, variance, and skewness). Table 7 Column (3) reports estimation results of Equation (1) in the entropy-balancing matched sample. Consistent with findings in the full sample, the coefficient of *r_PastDue%* is negative and significant. Untabulated tests show that the treatment and matched control groups are balanced on all three moments for all covariates. These results indicate that the negative association between late payments and future performance is robust to potential nonlinear relations with underlying determinants.

4. CONCLUSION

Despite the importance of payment timeliness to the success of trade credit relationships, there is little that is publicly disclosed regarding the status of a buyer's trade credit accounts. In this study, we use proprietary disclosure by suppliers to measure the percentage of trade credit payments that are past due and examine its informativeness about future firm financial performance.

In principle, the timeliness of payment of trade credit could be either a positive or negative indicator of future firm performance. If late payments reflect a firm's underlying liquidity issues, then late payments should be negatively associated with future performance. If, however, buyers delay payments to suppliers to fund profitable investment opportunities, the association should be positive.

We find that late payments are negatively associated with the next quarter's ROA and sales growth. Furthermore, we investigate default risk, and we find that past-due trade credit is strongly associated with negative changes in credit ratings and positively associated with subsequent bankruptcies and the issuance of going concern opinions. Finally, we investigate whether this information is reflected in subsequent stock prices. Returns around the next quarter's earnings announcement are negatively associated with percentages of past-due trade credit. Additionally, the percentage of past-due trade credit is negatively associated with risk-adjusted returns in the next month.

Our evidence that payment timeliness is informative about firms' prospects is relevant to the debate about whether to expand the disclosure about trade credit information. These findings suggest that increased disclosure of trade credit information would be useful for trade partners and investors. As such, these findings are relevant to standard setters and policy makers in weighing the costs and benefits of increasing transparency in trade relationships.

Appendix A

Thank you Inbox ×

James Starkey [redacted]

Thu, Sep 3, 2:29 PM (4 days ago)

Thank you for taking the time to present your research project "Do Trade Creditors Possess Private Information? Evidence from Firm Performance" and discuss your views on reverse factoring with our team. Your presentation and the following discussion provided useful inputs for the FASB's ongoing research in this area.

We appreciate your willingness to contribute to the standard setting process.

Regards,
James

James Starkey
Project Manager

FASB FINANCIAL ACCOUNTING STANDARDS BOARD

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Appendix B: Variable Definitions[24]

Variable Name	Definition
Trade Credit Variables	
TradeCredit	Average amount of total trade credit received in each month of quarter *q*.
OnTime	Average amount of on time trade credit outstanding at the end of each month in quarter *q*.
PastDue	Average amount of past due trade credit outstanding at the end of each month in quarter *q*.
TradeCredit/AP	Total trade credit deflated by the buyer's accounts payable at the end of quarter *q*.
PastDue%	Percentage of trade credit that is past due, value-weighted by total trade credit in each of the three months in quarter *q*.
Accounting and Financial Variables	
AT	Buyer's total assets at the end of quarter *q*.
MVE	Buyer's market value of equity at the end of quarter *q*. *SIZE* is the natural logarithm of *MVE*.
B/M	Buyer's book-to-market ratio at the end of quarter *q*.
AP/AT	Buyer's accounts payable deflated by total assets at the end of quarter *q*.
GrowAT	Buyer's growth of total assets in quarter *q*. Growth of total assets = (ending total assets - beginning total assets) / beginning total assets.
Cash/AT	Buyer's cash and cash equivalents deflated by total assets at the end of quarter *q*.
Cash/CL	Buyer's cash and cash equivalents deflated by current liabilities at the end of quarter *q*.
CFO/CL	Buyer's cash flow from operations divided by average current liabilities in quarter *q*.
Leverage	Buyer's total liabilities divided by total assets at the end of quarter *q*.
Distress	A categorical variable for default risk of the buyer based on its Altman Z-score in quarter *q*. *Distress* = 1 if Z-score < 1.8, 0.5 if 1.8 <= Z-score <= 2.99, and 0 if Z-score > 2.99.
AdjAccrual	Buyers' industry-adjusted current accruals in quarter *q*. Current accruals = (income before extraordinary items - cash flow from operations) / total assets.
ROA	Buyers' return on assets in quarter *q*, calculated as income before extraordinary items divided by average total assets in quarter *q*. *ROA_q+1* is the return on assets in quarter *q+1*.

[24] In millions USD.

∆Sales	Seasonal changes in sales in quarter *q*, calculated as (sales of quarter *q* - sales of quarter *q-4*)/ total assets at the end of quarter *q*. ∆*Sales_q+1* is the seasonal change in sales in quarter *q+1*.
EarnSurp	Buyer's earnings surprise of quarter *q*, calculated as the actual earnings per share of quarter *q* as reported by I/B/E/S minus the consensus analyst earnings forecast, scaled by stock price at the end of quarter *q*. When consensus analyst forecast is not available, the announced earnings per share of quarter *q-4* replaces consensus analyst forecast in the calculation of *EarnSurp*.
CAR[-1, +1]_q+1	Buyer's market-adjusted cumulative abnormal returns in the [-1, +1] window around the earnings announcement of quarter *q+1*.
CAR[-3, +3]_q+1	Buyer's market-adjusted cumulative abnormal returns in the [-3, +3] window around the earnings announcement of quarter *q+1*.
Default Risk Variables	
CreditRating_chg[25]	Changes in the buyer's S&P credit rating code in the six months after the end of quarter *q*. A positive (negative) change indicates credit rating upgrade (downgrade).
CreditRating_recent	Buyer's most recent S&P credit rating before the end of quarter *q*.
Bankruptcy	An indicator variable of whether the buyer files for bankruptcy in the six months after the end of quarter *q*.
GoingConcern_next	An indicator variable of whether the buyer receives a going concern opinion in the six months after the end of quarter *q*.
GoingConcern_recent	An indicator variable of whether the buyer received a going concern opinion in the most recent audit report before quarter *q*.
Big4	An indicator variable of whether the buyer's most recent audit opinion before quarter *q* was issued by a big 4 auditor (PwC, E&Y, KPMG, Deloitte)
Risk Factors	
MktRf	The market excess return. Risk factors are downloaded from Ken French’s website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
SMB	The size factor.
HML	The value factor.
UMD	The momentum factor.

[25] See Appendix C for the matching of numeric credit rating codes to letter ratings.

Appendix C: Credit Rating Codes

Code	Rating	Description
-2	AAA	The highest issuer credit rating assigned by Standard & Poor's, the AAA rating indicates an extremely strong capacity of the obligor to meet its financial commitments.
-4	AA+	AA indicates a very strong capacity to meet financial commitments, and differs from the highest rating only in small degree.
-5	AA	AA indicates a very strong capacity to meet financial commitments, and differs from the highest rating only in small degree.
-6	AA-	AA indicates a very strong capacity to meet financial commitments, and differs from the highest rating only in small degree.
-7	A+	A indicates a strong capacity to meet financial commitments, but it is somewhat more susceptible to adverse effects of changes in circumstances and economic conditions than obligors in higher-rated categories.
-8	A	A indicates a strong capacity to meet financial commitments, but it is somewhat more susceptible to adverse effects of changes in circumstances and economic conditions than obligors in higher-rated categories.
-9	A-	A indicates a strong capacity to meet financial commitments, but it is somewhat more susceptible to adverse effects of changes in circumstances and economic conditions than obligors in higher-rated categories.
-10	BBB+	BBB indicates an adequate capacity to meet financial commitments. However, adverse economic conditions or changing circumstances are more likely to lead to a weakened capacity of the obligor to meet its financial commitments.
-11	BBB	BBB indicates an adequate capacity to meet financial commitments. However, adverse economic conditions or changing circumstances are more likely to lead to a weakened capacity of the obligor to meet its financial commitments.
-12	BBB-	BBB indicates an adequate capacity to meet financial commitments. However, adverse economic conditions or changing circumstances are more likely to lead to a weakened capacity of the obligor to meet its financial commitments.
-13	BB+	BB indicates less vulnerability in the near-term than other lower-rated obligors. However, the obligor faces major ongoing uncertainties and exposure to adverse business, financial, or economic conditions which could lead to an inadequate capacity to meet its financial commitment.
-14	BB	BB indicates less vulnerability in the near-term than other lower-rated obligors. However, the obligor faces major ongoing uncertainties and exposure to adverse business, financial, or economic conditions which could lead to an inadequate capacity to meet its financial commitment.

-15	BB-	BB indicates less vulnerability in the near-term than other lower-rated obligors. However, the obligor faces major ongoing uncertainties and exposure to adverse business, financial, or economic conditions which could lead to an inadequate capacity to meet its financial commitment.
-16	B+	B is more vulnerable than a "BB"-rated obligor, but the obligor currently has the capacity to meet its financial commitments. Adverse business, financial, or economic conditions will likely impair the obligor's capacity or willingness to meet its financial commitments.
-17	B	B is more vulnerable than a "BB"-rated obligor, but the obligor currently has the capacity to meet its financial commitments. Adverse business, financial, or economic conditions will likely impair the obligor's capacity or willingness to meet its financial commitments.
-18	B-	B is more vulnerable than a "BB"-rated obligor, but the obligor currently has the capacity to meet its financial commitments. Adverse business, financial, or economic conditions will likely impair the obligor's capacity or willingness to meet its financial commitments.
-19	CCC+	CCC indicates that the obligor is currently vulnerable and is dependent upon favorable business, financial, and economic conditions to meet its financial commitments.
-20	CCC	CCC indicates that the obligor is currently vulnerable and is dependent upon favorable business, financial, and economic conditions to meet its financial commitments.
-21	CCC-	CCC indicates that the obligor is currently vulnerable and is dependent upon favorable business, financial, and economic conditions to meet its financial commitments.
-23	CC	Currently highly vulnerable.
-27	D	Default. Standard & Poor's believes the default will be a general default and the obligor will fail to pay all or substantially all of its obligations as they come due.
-29	SD	Selective Default. Standard & Poor's believes the obligor has selectively defaulted on a specific issue but will continue to meet its obligations on other issues.

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Table 1 – Sample Description

Panel A: Sample Selection

		# of Observations	# of Distinct Buyers
	All buyer-month observations from July 2002 to December 2017	2,332,947	32,706
minus:	Buyers not traded in NYSE, AMEX or NASDAQ	(1,830,536)	(26,645)
minus:	Financial firms	(65,645)	(1,016)
	Monthly Sample (buyer-months)	**436,766**	**5,045**
minus:	Averaging monthly trade credit in each fiscal quarter	(292,290)	(1,218)
minus:	Buyer-quarters without valid financial data	(22,378)	(667)
	Final Sample (buyer-quarters)	**122,098**	**4,176**

Panel B: Sample Distribution by Year

Year	# of Buyer-quarters	# of Distinct Buyers
2002	1,138	880
2003	4,933	1,577
2004	6,086	1,805
2005	6,577	1,938
2006	7,152	2,092
2007	7,878	2,277
2008	8,477	2,350
2009	8,829	2,420
2010	8,900	2,409
2011	8,747	2,358
2012	8,758	2,336
2013	8,910	2,398
2014	9,001	2,417
2015	9,091	2,463
2016	8,985	2,452
2017	8,636	2,342
Total	**122,098**	

Panel C: Sample Distribution by Industry

Industry Name	# of Buyer-quarters	Distinct Buyers		Distinct Firms in the Stock Universe		
		#	%	#	%	% excluding Finance
Consumer NonDurables	8,291	239	5.7%	357	4.1%	5.1%
Consumer Durables	4,104	112	2.7%	187	2.1%	2.7%
Manufacturing	17,843	483	11.6%	698	8.0%	9.9%
Oil, Gas, and Coal Extraction and Products	6,284	213	5.1%	355	4.1%	5.0%
Chemicals and Allied Products	4,436	131	3.1%	177	2.0%	2.5%
Business Equipment	25,786	1,017	24.4%	1850	21.2%	26.3%
Telephone and Television Transmission	3,533	135	3.2%	245	2.8%	3.5%
Utilities	4,318	110	2.6%	142	1.6%	2.0%
Wholesale, Retail, and Some Services	16,241	499	11.9%	711	8.1%	10.1%
Healthcare, Medical Equipment, and Drugs	15,247	703	16.8%	1206	13.8%	17.1%
Finance			0.0%	1712	19.6%	
Other	16,015	534	12.8%	1105	12.6%	15.7%
Total	**122,098**	**4,176**		**8,745**		

This table describes the sample selection and distribution. Panel A reports the sample selection process. Panel B reports the distribution of the sample for each year. Panel C reports the distribution of the sample across the 12 Fama–French industries. The stock universe includes all stocks listed on NYSE, AMEX, and NASDAQ between 2002 and 2017.

Table 2 – Descriptive Statistics

Panel A – Trade Credit Information

	N	Mean	Median	StdDev	Q1	Q3
TradeCredit ($m)	122,098	6.649	0.227	51.225	0.026	1.673
OnTime($m)	122,098	5.565	0.155	45.977	0.016	1.255
PastDue ($m)	122,098	1.084	0.047	7.612	0.005	0.336
TradeCredit/AP	122,012	2.24%	0.55%	11.46%	0.12%	1.90%
PastDue%	122,098	27.01%	22.26%	22.34%	10.45%	37.80%

Panel B – Financial, Default Risk, and Stock Return Information

	N	Mean	Median	StdDev	Q1	Q3
AT ($m)	122,098	5373	855	17861	240	3288
MVE ($m)	122,098	6161	914	23888	236	3401
B/M	122,098	3.027	0.442	552.585	0.255	0.708
AP/AT	122,098	8.20%	5.93%	7.80%	3.06%	10.67%
GrowAT	122,098	2.42%	0.88%	17.15%	-1.88%	3.91%
Cash/AT	122,098	17.15%	9.74%	19.39%	3.12%	24.06%
CFO/CL	122,098	11.91%	11.63%	31.77%	1.50%	23.72%
Leverage	122,098	51.95%	50.53%	27.91%	33.56%	66.37%
Distress	122,098	54.06%	50.00%	43.99%	0.00%	100.00%
AdjAccrual	122,098	-0.22%	0.09%	6.18%	-1.43%	1.58%
ROA	122,098	0.20%	1.03%	6.01%	-0.13%	2.14%
Δ*Sales*	122,098	1.35%	1.19%	7.98%	-0.64%	3.72%
CreditRating_chg	54,962	-2.09%	0.00%	63.29%	0.00%	0.00%
CreditRating_recent	54,987	-13.142	-13.000	3.606	-16.000	-11.000
Bankruptcy	122,098	0.10%	0.00%	3.19%	0.00%	0.00%
GoingConcern_next	118,988	0.80%	0.00%	8.93%	0.00%	0.00%
GoingConcern_recent	119,353	1.22%	0.00%	11.00%	0.00%	0.00%
Big4	119,353	80.93%	100.00%	39.28%	100.00%	100.00%
EarnSurp	95,164	-0.18%	0.05%	26.05%	-0.05%	0.22%
CAR[-1, +1]_q+1	93,905	0.18%	0.13%	9.23%	-4.10%	4.60%
CAR[-3, +3]_q+1	93,905	0.18%	0.21%	10.85%	-4.90%	5.30%

This table reports descriptive statistics for the full quarterly sample. Panel A reports statistics of trade credit information. Panel B reports financial, default risk, and stock return information. Dollar amounts are in millions USD. Definitions for all variables are available in Appendix B. See Appendix C for details on the matching of letters to the numeric credit rating codes.

Table 3 – Late Payments and Future Performance

Y =	(1) ***ROA_q+1***	(2) **Δ*Sales_q+1***
r_PastDue%	-0.292***	-0.101***
	(-8.81)	(-3.15)
ROA	0.522***	
	(37.07)	
Δ*Sales*		0.672***
		(129.57)
SIZE	0.002***	0.000*
	(20.25)	(1.72)
B/M	-0.005***	-0.006***
	(-9.81)	(-13.39)
AP/AT	0.011***	0.010***
	(3.92)	(3.60)
GrowAT	0.000	0.052***
	(0.02)	(26.64)
Cash/AT	-0.030***	-0.005***
	(-20.45)	(-5.89)
CFO/CL	0.015***	-0.007***
	(10.79)	(-10.43)
Leverage	-0.002	-0.004***
	(-1.41)	(-4.92)
Distress	-0.010***	-0.002***
	(-19.16)	(-5.77)
AdjAccrual	-0.052***	-0.003
	(-4.50)	(-0.59)
N	122,098	122,098
Adjusted R-squared	50.15%	55.34%

This table reports the results of estimating Equation (1). The dependent variables are the return on assets (*ROA)* and seasonal changes in sales (Δ*Sales*) in quarter *q+1*. *r_PastDue%* is the quintile rank of the buyer's past-due proportion in quarter *q* and scaled to [0, 1]. For conciseness, the coefficients of *r_PastDue%* are expressed in percentage. All regressions include industry and year–quarter fixed effects. Standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4 – Late Payments and Default Risk

	(1)	(2)	(3)
Y =	***CreditRating_chg***	***Bankruptcy***	***GoingConcern_next***
r_PastDue%	-26.106***	72.666**	41.618***
	(-4.38)	(2.05)	(2.82)
CreditRating_recent	-0.203***		
	(-13.49)		
GoingConcern_recent			2.485***
			(12.15)
Big4			0.374***
			(2.96)
SIZE	0.330***	-0.393***	-0.690***
	(11.49)	(-3.93)	(-11.73)
B/M	-0.777***	0.518**	0.031
	(-11.64)	(2.05)	(0.35)
AP/AT	2.251***	-5.684***	-0.453
	(5.25)	(-2.91)	(-0.62)
GrowAT	0.468**	-2.240**	-0.970***
	(2.57)	(-2.16)	(-2.76)
Cash/AT	0.121	-1.826	-0.060
	(0.58)	(-1.46)	(-0.20)
CFO/CL	1.822***	-1.221*	-2.079***
	(12.74)	(-1.74)	(-7.58)
Leverage	-1.455***	5.687***	1.582***
	(-8.62)	(7.17)	(7.16)
Distress	0.055	-0.423	1.979***
	(0.67)	(-0.61)	(5.99)
AdjAccrual	8.252***	-4.765***	-5.977***
	(13.51)	(-2.59)	(-7.88)
N	49,410	68,231	112,190
Pseudo R-squared	7.35%	30.19%	49.29%

This table reports the results of estimating Equation (2) for three default risk measures. Column (1) is estimated using ordered logit, while Columns (2) and (3) are estimated using logit. *r_PastDue%* is the quintile rank of the buyer's past-due proportion in quarter *q* and scaled to [0, 1]. For conciseness, the coefficients of *r_PastDue%* are expressed in percentage. All regressions include industry and year–quarter fixed effects. Standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5 – Late Payments and Stock Returns

Panel A: Abnormal Portfolio Returns

***Y* =**	***Ret_L-H***	
	(1)	(2)
	Fama-French 3-factor model	**Carhart 4-factor model**
Alpha	0.4448***	0.4267***
	(3.41)	(3.26)
MktRf	-0.1279***	-0.1043***
	(-2.99)	(-2.76)
SMB	0.1618***	0.1558**
	(2.63)	(2.54)
HML	0.0440	0.0715
	(0.72)	(1.16)
UMD		0.0590*
		(1.67)
N	186	186
Adjusted R-squared	5.95%	7.07%

Panel A reports monthly abnormal portfolio returns based on *PastDue%* in the monthly sample. At the beginning of each month, stocks are ranked in ascending order of *PastDue%* of the previous month and sorted into five quintile portfolios. Within a given portfolio, stocks are value weighted and rebalanced every month. *Ret_L-H* is the monthly hedging return from a zero-cost portfolio that buys the bottom-quintile stocks and short-sells the top-quintile stocks. Alpha is the intercept on a regression of *Ret_L-H* on risk factors using the Fama-French (1993) 3-factor model or Carhart (1997) 4-factor model. Alpha is reported in percentage. The sample includes 186 months from July 2002 to December 2017. T-statistics are calculated using Newey-West standard errors with three lags and reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel B: Abnormal Returns Around Earnings Announcements

Y =	(1) ***CAR[-1, +1]_q+1***	(2) ***CAR[-3, +3]_q+1***
r_PastDue%	-0.235***	-0.264***
	(-2.75)	(-2.62)
EarnSurp	-0.100***	-0.124***
	(-2.67)	(-2.70)
SIZE	0.000	0.000*
	(0.67)	(1.77)
B/M	0.002**	0.006***
	(2.07)	(4.28)
AP/AT	-0.010*	-0.006
	(-1.94)	(-0.92)
GrowAT	-0.001	-0.003
	(-0.17)	(-0.68)
Cash/AT	-0.007***	-0.007***
	(-3.36)	(-2.67)
CFO/CL	-0.001	-0.002
	(-0.35)	(-0.92)
Leverage	0.010***	0.016***
	(4.50)	(5.80)
Distress	-0.005***	-0.007***
	(-5.04)	(-5.46)
AdjAccrual	-0.001	-0.010
	(-0.13)	(-0.76)
N	93,905	93,905
Adjusted R-squared	0.59%	0.96%

Panel B reports the results of estimating Equation (3) for two cumulative abnormal return measures. *r_PastDue%* is the quintile rank of the buyer's past-due proportion in quarter *q* and scaled to [0, 1]. For conciseness, the coefficients of *r_PastDue%* are expressed in percentage. All regressions include industry and year–quarter fixed effects. Standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6 – Cross-sectional Analyses

Panel A – Short Term Liquidity

	Cash/CL		***CFO/CL***	
	Low	*High*	*Low*	*High*
r_PastDue%	-0.397	-0.247	-0.381	-0.198
	(-8.948)***	(-5.591)***	(-7.449)***	(-5.428)***
Diff. (High-Low)	0.150 **		0.183 ***	
Pred. Sign	+		+	
P of diff.	0.013		0.004	
SUR Chi-square	6.12		8.43	

Panel B – Long Term Solvency

	Leverage		***Distress***	
	Low	*High*	*Low*	*High*
r_PastDue%	-0.224	-0.364	-0.165	-0.418
	(-5.491)***	(-7.055)***	(-3.883)***	(-7.010)***
Diff. (High-Low)	-0.140 **		-0.253 ***	
Pred. Sign	-		-	
P of diff.	0.030		0.001	
SUR Chi-square	4.70		11.80	

This table reports the results of estimating Equation (1) in subsamples. The dependent variable is the return on assets (*ROA)* in quarter *q+1*. *r_PastDue%* is the quintile rank of the buyer's past-due proportion in quarter *q* and scaled to [0, 1]. For conciseness, only coefficients of *r_PastDue%* are tabulated. In Panel A, subsamples are partitioned at the median each quarter by *Cash/CL* (cash deflated by current liabilities) or *CFO/CL* (cash flow from operations deflated by current liabilities) in quarter *q*. In Panel B, subsamples are partitioned at the median each quarter by *Leverage* (total liabilities divided by total assets) or *Distress* (an ordinal variable of default risk based on the Altman Z-score) in quarter *q*. The difference in coefficients of *r_PastDue%* across subsamples is tested by seemingly unrelated regressions (*SUR*). All regressions include industry and year–quarter fixed effects. Standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7 – Robustness Tests

Y = ROA_q+1	(1) ***With Firm FE***	(2) ***Drop Financial Crisis***	(3) ***Entropy-Balanced Sample***
r_PastDue%	-0.115***	-0.286***	-0.324***
	(-3.18)	(-8.38)	(-9.00)
ROA	0.248***	0.543***	0.521***
	(15.02)	(38.00)	(35.39)
SIZE	0.003***	0.002***	0.002***
	(10.59)	(19.33)	(20.65)
B/M	-0.013***	-0.004***	-0.004***
	(-6.93)	(-7.79)	(-8.31)
AP/AT	0.053***	0.010***	0.010***
	(12.47)	(3.75)	(3.40)
GrowAT	0.012***	-0.001	-0.001
	(9.31)	(-0.35)	(-0.49)
Cash/AT	0.006*	-0.029***	-0.032***
	(1.88)	(-19.01)	(-20.78)
CFO/CL	0.004**	0.015***	0.015***
	(2.49)	(9.93)	(9.94)
Leverage	-0.003	-0.002	-0.002
	(-1.36)	(-1.43)	(-1.38)
Distress	-0.005***	-0.010***	-0.011***
	(-6.29)	(-17.49)	(-18.37)
AdjAccrual	-0.020**	-0.037***	-0.075***
	(-2.65)	(-3.14)	(-6.19)
N	122,098	96,914	122,098
Adjusted R-squared	57.70%	53.60%	50.57%

This table reports results of three robustness tests for Equation (1). The dependent variable is the return on assets (*ROA)* in quarter *q+1*. *r_PastDue%* is the quintile rank of the buyer's past-due proportion in quarter *q* and scaled to [0, 1]. For conciseness, the coefficients of *r_PastDue%* are expressed in percentage. In Column (1), firm fixed effects are added and standard errors are clustered by quarter. In Column (2), observations during 2007–2009 are removed from the sample. In Column (3), the sample is entropy balanced on the first three moments (mean, variance, and skewness) of all control variables. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.