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ABSTRACT

Theories of customer supplier relationships hold that the private information of suppliers about buyers explains the use of trade credit even when there is a competitive banking sector. If suppliers possess private information about their buyers, then the buyer's order size and ability to pay on time should reflect that information. Using a novel dataset of trade credit relationships, we test whether suppliers have private information about their buyers. Consistent with suppliers possessing private information, we find that the amount of trade credit that a supplier offers to a buyer and the ability of the buyer to pay the trade credit on time are both associated with future buyer abnormal stock returns.

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1. INTRODUCTION

Trade credit provided by suppliers is an important source of external finance for U.S. firms. About a quarter of corporate debt is trade credit, and the size of this trade credit is roughly three times the size of bank loans (Rajan and Zingales 1995; Barrot 2016; Ivashina, Iverson, and Smith 2016).[1] Despite the importance of trade credit for business-to-business contracting, relatively little is understood about the value of the information relevant to these credit decisions. We investigate whether suppliers have private information about their buyers by testing whether proxies for this information predict future stock returns. Specifically, we test whether the amount of trade credit a supplier sells to its buyer, and the historical ability of a buyer to pay suppliers on time, predict future stock returns?

Existing research offers two main explanations for the existence and widespread use of trade credit. The first is that suppliers offer trade credit as a financing of last resort (when financing via bank credit or securities issuance is unavailable). The second is that suppliers hold an informational advantage about their customers' businesses over other credit providers. Most empirical studies lend support to the financing-of-last-resort

[1] Rajan and Zingales (1995) find that 22.8% of public firms' liabilities are trade credit, whereas Ivashina, Iverson, and Smith (2016) look at a set of firms entering Chapter 11 bankruptcy and find that 22.5% of their liabilities are trade credit. Based on the U.S. Flow of Funds Accounts, Barrot (2016) estimates that aggregate accounts payable is three times as large as bank credit and fifteen times as large as commercial paper. Of course, private firms appear to depend more heavily on trade credit than do public firms (Abdulla, Dang, and Khurshed 2017).

explanation. For example, firms that have weak relationships with banks tend to rely more on trade credit (Petersen and Rajan 1997), and trade credit increases when bank credit contracts (Nilsen, 2002). Similarly, firms from countries with less developed banking systems are more likely to use trade credit (Fisman and Love 2003).

Models of trade credit are typically based upon the premise that the supplier possesses an informational advantage about the customer (Fabbri and Menichini 2010). This private information comes in two forms. The first is that by offering trade credit, the supplier acts on good information about the buyer that the market does not know (Biais and Gollier 1997; Chod 2016; Lee and Stowe 1993). The second is that the very act of providing trade credit improves the customer's competitive position through financing.[2] This private information is impounded in the trade credit order's size, timing, and the ability of the buyer to avoid delinquency on the order (Petersen and Rajan, 1997).[3]

Our goal in this study is to identify whether trade credit in fact reflects private information. We provide direct tests of the informational content of trade credit using a proprietary dataset on trade credit offerings between suppliers and buyers. These data

[2] Because the more trade credit a firm receives, the more trade credit that firm extends (Petersen and Rajan 1997; Fabbri and Klapper 2008), receiving trade credit demonstrates a firm's ability to make sales in the future. It is also indicative of a firm's ability to improve its market power through its own offering of trade credit (Brennan, Maksimovic, and Zechner 1988; Giannetti, Serrano-Velarde, and Tarantino 2017).

[3] The decision to publicly disclose information about customers has been shown to be related to proprietary costs (Ellis, Fee, and Thomas 2012).

include monthly records of accounts receivable for firms selling to publicly traded companies. We can also observe the proportion of offered trade credit that is on time versus that which is delinquent on timely credit payments, or past due. Our data cover accounts payable for 5,278 distinct public firms, comprising 422,591 firm months for the years 2002–2017. The data are assembled from the accounts receivable files shared by anonymous supplying firms. On average, we aggregate files from 12.28 suppliers and obtain a total trade credit of $6.09 million for each buyer–month. On an average basis, 27.23% of the total trade credit is overdue.

To test whether trade creditors have private information, we first examine whether the change in the amount of trade credit offered by suppliers is associated with buyers' future stock returns. If trade creditors have private information, we expect a positive correlation for several reasons. First, firms that receive new trade credit are likely to be more creditworthy (Klapper, Laeven, and Rajan 2011; Murfin and Njoroge 2014). Second, new trade credit offered to a firm is an indicator of greater market power (Brennan, Maksimovic, and Zechner 1988; Giannetti, Serrano-Velarde, and Tarantino 2017). Third, an increase in the trade credit that a firm receives positions the firm to extend more trade credit (Petersen and Rajan 1997; Fabbri and Klapper 2008), which can improve sales. So if suppliers have private information about their buyers, we predict that a firm that is offered greater trade credit will tend to have better future fundamental and return performance.

Consistent with this hypothesis, we find that a long-short portfolio that buys stocks with larger amounts of changes in trade credit and sells stocks with low change in trade credit outperforms different benchmarks (CAPM, Carhart 1997 and Fama-French 2015) by 0.34–0.43% per month, or 4.08–5.16% annually, with significance at the 5% level. These results suggest that the supplier holds private information about the buyer, since the amount of trade credit offered is associated with future stock returns.

A firm's ability to remain a going concern is important both to equity holders as well as creditors. While insider assessments of a firm's financial health are strong indicators for future returns (Foster, 1973; Patell 1976; Ajinkya and Gift 1984), so are indicators based on outside assessments. Indeed, the opinions of outside auditors are strongly predictive of future returns, whether in the form of a going concern assessment (Firth 1978; Fleak and Wilson 1994; Jones 1996; Taffler, Lu, and Kausar 2004), or an auditor's disclosure of an internal control material weakness (ICMW) (Ashbaugh-Skaife, Collins, Kinney, and LaFond 2009).

The ability of a firm to pay its credit bills on time should also be an indicator of the future fundamental performance of a firm. When a firm fails to pay trade credit on time, it risks its ability to obtain trade credit from that supplier in the future and, potentially, its ability to trade with that upstream firm at all. Furthermore, the contract between the supplier and the buyer often stipulates penalties (discounts) for paying late (early). This makes such a decision very costly, both implicitly and explicitly, since it sacrifices future performance. Whether a signal of bad future prospects, or an indicator that a firm will be unable to trade as effectively in the future, we predict that that a firm's timeliness in paying trade credit should be positively related to a firm's future returns.

We find that the proportion of past due trade credit as a percentage of total trade credit is a negative predictor of future stock returns. A long–short portfolio that buys stocks with a low proportion of past due trade credit and sells stocks with a high proportion of past due trade credit outperforms the various benchmarks by 0.30%–0.34% per month, or 3.60% to 4.08% annually, with significance at the 5% level. The returns are derived mainly from the firms with a low proportion of past due trade credit. The abnormal returns for firms that pay their trade credit on time exceed the benchmark by 0.19%–0.26% per month. Similarly, these results suggest that the supplier possess private information about the buyer, since the percentage of timely payments by the buyer is associated with future stock returns.

One possible concern is that our results are driven by outlier years in our sample due to the role trade credit implicitly plays in monetary policy (Meltzer 1960), and due to the dynamics of trade credit use during periods of monetary tightening (Choi and Kim 2005) or in times of crisis (Garcia-Appendini and Montoriol-Garriga 2013). We therefore test whether our findings are robust to excluding peak years of the financial crisis (2007-2009), and we find that our results still hold. We find that the association between trade credit or the proportion of past due trade credit, and stock returns is slightly stronger in this setting. A long–short portfolio that buys stocks with high change in trade credit (low proportion of past due trade credit) and sells stocks with a low change in trade credit (high proportion of past due trade credit) outperforms the various benchmarks by 0.40%–0.48% (0.37%–0.44%) per month and is significant at the 5% (1%) level.

To understand the sources of predictability of future stock returns and trade credit information, we conduct various subsample analyses based on three constructs. First, we make a comparison based on how important the supplier is to the buyer. If the supplier is more important to the buyer, we predict that the association between trade credit and returns will be stronger. Second, we test whether the ability of the firm to pay its short-term obligations, and the capacity to meet its long-term financial commitment, are moderators of the association between trade credit and abnormal returns. Low liquidity and solvency risk implies that trade credit is less likely to be the buyer's financing of last resort and more likely driven by the supplier's private information. Thus, we predict that low liquidity and solvency risk leads to stronger return predictability of trade credit. Finally, we predict that growth firms gain more from trade credit than value firms, since a growth firm's demand for more trade credit signals increased demand for the product and increased confidence in the creditworthiness in the eyes of the supplier.

The evidence is consistent with these predictions. For example, when we partition the sample based on how important the supplier is to the buyer, we find stronger results when the percentage of the total trade credit that is contributed by the major supplier out of the total trade credit (*Major%*) is high. A long–short portfolio that buy stocks with high on-time trade credit and sell stocks with low on-time trade credit when *Major%* is high outperforms the Fama French (2015) 5-factor model by 0.95% per month, or 11.40% annually and is statistically significant at the 1%. The return for the low *Major%* portfolio is equal to 0.06% per month and is not statistically significant.

The finding that that trade credit predicts returns suggests that trade credit is associated with future accounting performance. Consistent with this, we find that the change in monthly trade credit is positively correlated with changes in the upcoming quarter's accounts payable, inventory, earnings, and revenues. These findings are consistent with the results of the positive association between trade credit and stock returns, and they suggest that suppliers have private information about their buyers.

The paper possibly closest to ours is Ivashina and Iverson (2018),[4] which investigates bankruptcy outcomes. They find that creditors' decisions to factor receivables is predictive of lower recovery rates on the part of other creditors, and this holds more strongly for more opaque distressed firms. The fact that some suppliers do this ahead of less informed suppliers and ahead of other creditors is indicative of the significant private information they hold about the distressed firm. Through our portfolio returns tests, we provide evidence that suppliers hold private information relevant to outcomes in a general context, i.e., not limited to distressed firms.

While our goal is to test whether trade credit suppliers possess private information about their customers, our paper relates to a growing literature on economically linked firms and return predictability. Stock prices do not incorporate customer returns in a timely manner (Cohen and Frazzini 2008; Menzly and Ozbas 2010; Pandit, Wasley, and Zach 2011), bankruptcy shocks cut both ways across customer–supplier linkages (Hertzel et al. 2008) as well as strategic alliances (Boone and Ivanov 2012), and customers are gravely affected by suppliers that experience natural disasters (Barrot and Sauvagnat

[4] Jacobson and Schevdin (2015) investigate the effects that customer–supplier relationships have on the propagation of bankruptcy.

2016). Ali and Hirshleifer (2018) provide evidence suggesting that firm-linkage return anomalies are subsumed by return spillovers associated with firms that are linked by overlap in analyst coverage. There is also evidence that cross-industry merger activity is highly related with the customer–supplier network topology of the market (Ahern and Harford, 2014).

Whereas these previous papers investigate the extensive margin of trade activity and its relationship with return predictability, we investigate the intensive margin, or the extent of the trade relationship. Further, this literature shows that economic links are information conduits, but only from the perspective of attention-constrained investors. In this literature, firms need not have private information about their trade credit partners for these publicly known economic links to be relevant to predictability in returns (Cohen and Frazzini 2008). We show that suppliers themselves have private information.

To our knowledge, our paper provides the first large-sample evidence of the information advantage that suppliers of trade credit may have with respect to their customers. Trade credit and decisions made by suppliers with respect to trade credit are multifaceted accounting objects, as they are indicative not only of capital structure but also trade relationships. While the trading frictions common in conventional arm's-length financing can be mitigated by trade credit relationships, these relationships grow and can break down with time. Our findings show that information relevant to trade credit—both the amounts offered and whether buyers or debtors are delinquent—contains private information about the customer.

2. DATA

2.1 Sample selection and distribution

We obtain monthly records of trade credit from a proprietary data vendor. Various 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 identification information of the buyer, but the data vendor anonymizes the supplier to protect its clients' identities. Buyers' stock returns are obtained from the CRSP monthly return file, and financial data are obtained from the Compustat North American file.

Table 1 Panel A presents details of the sample selection. The initial sample from the data vendor includes monthly records of 502,847 distinct supplier–buyer pairs. For each buyer and for each month, we aggregate trade credit from all suppliers, which yields 32,749 distinct buyers and 2,342,262 buyer–months. To infer the information content of trade credit from stock returns, we restrict buyers to public companies listed on NYSE, AMEX, and NASDAQ. We exclude buyers without monthly stock return data from CRSP or without valid financial data from Compustat. To measure the new information conveyed by trade credit, we calculate seasonal changes in the size of trade credit and remove observations that lack a corresponding record in the same month in the previous year. The final sample contains 422,591 monthly trade credit records for 5,278 distinct buyers, from June 2002 to November 2017.

Table 1 Panel B presents the distribution of sample observations by year. The dataset covers 1,012 distinct buyers and 4,627 supplier–buyer pairs in 2002. The number of distinct buyers and distinct supplier–buyer pairs steadily increases in the next 15 years, with the only exception being the number in 2017, for which we lack one month's data. The 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 over the buyer's industry and compares it to the distribution of the stock universe. The stock universe includes all stocks listed on NYSE, AMEX, and NASDAQ during the sample period. Our sample firms cover 58.7% (5,278 / 8,998) of the stock universe. We define 12 industries using the Fama–French classification.[5] The sample distributes similarly to the stock universe, with slightly more firms from Manufacturing (9.5% versus 8.1%) and Wholesale, Retail, and Some Services (9.8% versus 8.0%) and fewer firms from Finance (16.0% versus 19.5%).

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

2.2 Variable measurement

For each buyer each month, we aggregate trade credit from all suppliers and we do this separately for each aging bucket. 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 normalize total trade credit by the buyer's assets as of the most recent fiscal year end (*TradeCredit/AT*). We also deflate trade credit by the buyer's accounts payable of the most recent fiscal year (*TradeCredit/AP*) to gauge the coverage of our dataset. From the balances in the aging buckets, we calculate the percentage of trade credit that is past due (*PastDue%*). We also report the number of suppliers (*N_Supplier*), the suppliers' Herfindahl–Hirschman index (*HHI*), the average number of months since suppliers started to offer trade credit to the buyer (*Avg_RelationLength*), and the average amount of trade credit offered by each supplier (*Avg_TradeCredit*).

Suppliers differ in their private information about the buyer, and a supplier that offers more trade credit is likely to be more informed.[6] Therefore, we identify the supplier that offers the most trade credit (the *major* supplier) and examine it separately from the remaining suppliers (the *minor* suppliers).[7] The historical amounts of trade credit are

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[6] Ivashina and Iverson (2018) find that, in a bankruptcy setting, suppliers that extend the most trade credit relative to their capacity sell receivables ahead of less-informed suppliers, indicating differential information advantages.

[7] If the buyer has only one supplier in a specific month, there will be no minor supplier. Our results are similar if we restrict to buyer observations that have at least two suppliers.

disclosed as accounts payables on balance sheets and are known by the market. To measure the new private information conveyed by trade credit, we calculate changes in trade credit from the same month in the previous year. The percentage of trade credit that is delinquent, on the other hand, is not publicly available in any mandated disclosures. Hence, we use the level, instead of the change, of this percentage to measure private information. Seasonal changes in total trade credit from the major supplier (minor supplier) is represented as *ΔTradeCredit_Major* (*ΔTradeCredit_Minor*) normalized by the buyer's total assets. The percentage of trade credit from the major supplier (minor supplier) that is past due is represented as *PastDue%_Major* (*PastDue%_Minor*).

Table 2 Panel A reports summary statistics of trade credit variables for all buyer–months. On average, each buyer receives trade credit from 12.28 suppliers for a total amount of $6.09 million, which accounts for 0.15% of the buyer's total assets. The mean percentage of trade credit that is past due ranges from 27.23% for the total amount to 3.08% for the amount past due for more than 90 days. The average ratio of trade credit to the buyer's accounts payable of the previous fiscal year is 2.23%, suggesting limited coverage by our dataset and limitations on inferences that can be drawn from the size of trade credit. Turning to the interaction among suppliers, both the Herfindahl–Hirschman index (*HHI*) and the percentage of trade credit contributed by the major supplier (*Major%*) indicate that trade credit is concentrated in the major supplier. This lends support to the notion that, relative to minor suppliers, the major supplier has more incentives and a greater ability to obtain private information about the buyer's future prospects.

3. RESEARCH DESIGN AND RESULTS

3.1 Trade credit size and stock returns

We first examine whether the change in the amount of trade credit offered by suppliers is positively associated with buyers' future stock returns. Firms that receive more trade credit are likely to be more creditworthy and have greater market power. Furthermore, the more trade credit a firm receives, the more trade credit that firm can extend, leading to higher sales.

To test this hypothesis, we examine the return predictive power of $\triangle$*OnTime_Major*, which is the change in on-time trade credit from the major supplier. We use this variable as a proxy for the private information in trade credit due to three reasons. First, levels of trade credit reflect historical information disclosed as accounts payable on balance sheets, and hence are known by the market. So the change in trade credit from the same month in the previous year captures the new information conveyed by our monthly trade credit records. Second, suppliers differ in their private information about the buyer. We focus on the major supplier that is likely to be more informed.[8] Last, the amount past due reflects trade credit received in the past. To examine the information content of trade credit received in the current period, we restrict our analysis to on-time trade credit.

We employ a portfolio approach to examine the return predictability of trade credit. For the end of every month t, we sort all buyers' stocks into five portfolios based on *△OnTime_Major.*[9] The top (bottom) portfolio contains stocks with the highest (lowest) *△OnTime_Major.* We then track stock performance over the following month and value weight stock returns within each portfolio.[10] For each month, we also construct a long–short portfolio that buys the top *△OnTime_Major* portfolio and sells the bottom *△OnTime_Major* portfolio (*H* - *L*). Portfolios are rebalanced every calendar month.

To control for known return predictors and factors, we compute alphas from a time-series regression of portfolio excess returns on monthly factor returns. For each portfolio, we compute alphas based on the CAPM model, the Carhart (1997) 4-factor model, and the Fama–French (FF) (2015) 5-factor model.[11] The alphas represent the

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[8] In a bankruptcy setting, Ivashina and Iverson (2018) find that suppliers who extend the most trade credit relative to their capacity sell receivables ahead of less-informed suppliers, indicating differential information advantage.

[9] We also tried sorting into three portfolios. Results are qualitatively similar (untabulated).

[10] 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).

[11] Factor returns are obtained from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

average monthly risk-adjusted abnormal returns earned by each portfolio. We predict alphas to be increasing in Δ*OnTime_Major*.

Table 3 reports the results of estimating alphas. A long–short portfolio that buy stocks with high Δ*OnTime_Major* and sells stocks with low Δ*OnTime_Major* outperforms the FF 5 factor monthly benchmark by 0.43% per month, or 5.16% annually and is statistically different from zero at the 5% level. The average monthly abnormal return for the portfolio of firms with the lowest Δ*OnTime_Major* (Portfolio L), is equal to -0.18%, but is not statistically different than zero (t-stat of -1.54). On the other hand, the average monthly abnormal return for firms with the highest Δ*OnTime_Major* (Portfolio H) is equal to 0.25% and is statistically different from zero at the 5% level.

We obtain similar results for the CAPM model and for the Carhart model. The monthly hedge returns are 0.37% and 0.34% respectively and are significant at the 5% level. We also find similar results when we drop micro stocks (stocks with market value less than $300 million). For example, the monthly hedge returns using the FF 5-factor model is equal to 0.39% and is significant at the 5% level.

The results in this section suggest that suppliers have private information regarding their customers. The firm's demand for trade credit and the supplier's decision to offer trade credit is associated with future abnormal stock returns. A long–short portfolio that buys stocks with a greater change in on-time trade credit and sell stocks with a smaller change in on-time trade credit outperforms the various benchmarks by 0.37–0.43% per month, or 4.44–5.16% annually. This finding corroborates conjectures made in the literature that suppliers hold valuable private information about their clients' overall quality (Biais and Gollier 1997) and about the quality of clients' products (Lee and Stowe 1993; Frank and Maksimovic 1998; Ng, Smith, and Smith 1999; Giannetti, Burkart, and Ellingsen 2011) likely due to cheaper monitoring of their buyers (Smith 1987).

3.2 Past due trade credit and stock returns

We next examine the ability of past due trade credit to predict returns. When a firm fails to pay trade credit in a timely manner, there are explicit penalties (e.g., losing a purchase discount) and implicit penalties (e.g., losing future trade credit from the supplier), both of which impede future performance. Since whether the buyer pays trade credit on time is not publicly disclosed, we posit that the failure to pay trade credit on time is negatively associated with future stock returns.

Specifically, we test the return predictive power of *PastDue%_Major*, which is the percentage of trade credit from the major supplier that is past due. Similar to the test of trade credit size, we focus on the major suppliers because they are more informed. Unlike the level of trade credit, the historical proportion of delinquent trade credit is not publicly available. Hence, we measure private information using the level of this percentage, instead of the change.

We construct trading portfolios based on *PastDue%_Major* and predict that monthly abnormal returns are negatively associated with *PastDue%_Major*. In Table 4, we find that a long–short portfolio that buys stocks with low past-due trade credit and sells stocks with high-past due trade credit outperforms the various benchmarks by 0.30–0.34% per month, or 3.60–4.08% annually The hedge returns for the full sample are statistically different than zero at the 5% level, and for the sample that excludes micro stocks, they are statistically significant at the 1% level. Most of the predictability of the returns derives from firms that pay their trade credit on time (i.e., a low *PastDue%_Major*). The abnormal returns from the low *PastDue%_Major* (Portfolio L) exceed the benchmark by 0.19–0.26% per month and is statistically different from zero at least at the 10% level.

These findings suggest that the suppliers have private information about their buyers in the form of the ability of the buyers to pay trade credit on time. The firm that pays its credit bills on time avoids costly penalties. The signal that past due credit provide about a buyer indicates how important trade credit relationships are for a firm (Biais and Gollier, 1997). These returns may also indicate the value of incentive alignment properties between downstream firms and other financial intermediaries provided by trade credit (Fabbri and Menichini 2016; Chod 2016).

3.3 Trade credit and stock returns – remove 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). Thus, it is interesting to examine whether the information that trade credit provides about firms' future returns applies throughout the time period or only in times of crisis. We now test whether our results are robust to excluding the years of the financial crisis. We study the effect that the financial crisis had on the association between trade credit and stock returns by removing from the sample all observations that occurred during the financial crisis (2007–2009).

Table 5 reports the results of this analysis. The results hold when removing the observations related to the financial crisis. A long–short portfolio that buys stocks with high on-time trade credit and sells stocks with low on-time trade credit outperforms the various benchmarks by 0.40–0.48% per month and is statistically different from zero at the 5% level.

The results also hold when considering the association between past due payments and stock returns. In fact, the abnormal return for the hedge portfolio is larger when excluding the financial crisis from the analysis. A long–short portfolio that buys stocks with a low percentage of past due trade credit and sells stocks with a high percentage of past due trade credit outperforms the various benchmarks by 0.37–0.44% per month, or 4.44–5.28% annually, and is statistically different from zero at the 1% level.

It might be argued that more informal financial intermediation such as the provision of trade credit is only informative in times of macroeconomic flux and turmoil when the need for trade credit becomes binding (Choi and Kim 2005). Nonetheless, the analysis in this section indicates that our conclusion that trade creditors have useful private information is robust to excluding the financial crisis.

3.4 Moderators of the relationship between trade credit and future returns

To understand the sources of predictability of future stock returns and trade credit information, we conduct various subsample analyses based on three constructs. First, we examine the effect of supplier concentration. If the supplier is more important to the buyer, we predict that the association between trade credit and return will be stronger. Second, we test whether short- and long-term liquidity risk affects return predictability. If the buyer is less likely to treat trade credit as financing of last resort, we predict the return relationship to be stronger. Finally, we predict that growth firms gain more from trade credit than value firms since the demand of growth firms for more trade credit signals increased demand for the product and increased belief in the creditworthiness of the growth firm in the eyes of the supplier.

The results of the subsample analyses are provided in Table 6. Panel A presents results of the supplier concentration construct. The first measure we use is the Herfindahl–Hirschman index (*HHI*). We partition the sample at the median by high and low *HHI*. High *HHI* suggests that the competition between the suppliers is concentrated. The results suggest that the association between trade credit and returns is stronger when the competition between the suppliers is concentrated. A long–short portfolio that buys stocks with high on-time trade credit and sells stocks with low on-time trade credit when *HHI* is high outperforms the FF5 benchmark by 0.95% per month, or 11.40% annually, and is statistically different from zero at the 1% level. The return for the low *HHI* portfolio is equal to 0.15% and is not statistically different from zero.

The second measure we use is the percentage of trade credit contributed by the major supplier (*Major%*). The results appear similar to the results using the *HHI* measure. A long–short portfolio that buys stocks with high on-time trade credit and sells stocks with low on-time trade credit when *Major%* is high outperforms the FF5 benchmark by 0.95% per month, or 11.40% annually, and is statistically different from zero at the 1% level.

Panel B presents the results of the short-term liquidity analyses. The first measure we use is *Cash Ratio*. We partition the sample at the median by high and low *Cash Ratio*. High *Cash Ratio* shows that the firm has a larger amount of cash relative to its current liabilities. The results suggest that the association between trade credit and returns is stronger when short-term liquidity is high. A long–short portfolio that buys stocks with high on-time trade credit and sell stocks with low on-time trade credit when *Cash Ratio* is high outperforms the FF5 benchmark by 0.72% per month, or 8.64% annually, and is statistically different from zero at the 1% level. Similar results are achieved when using another short-term liquidity measure: cash flow from operations deflated by current liabilities (*CFO/CL*).

Panel C presents the results of the long-term liquidity analyses. The first measure we use is the leverage ratio (*Leverage*). We partition the sample at the median by high and low *Leverage*. Low *Leverage* shows that the firm has lower liabilities relative to its assets. The second measure is an indicator variable that receives the value of one for high-default risk firms based on the Altman (1968) Z-score measure (*Distress*), and zero otherwise. The results suggest that the association between trade credit and returns is stronger when long-term liquidity is low.

Finally, Panel D presents results of subsample analyses based on the firm's growth. The first measure we use is book-to-market ratio (B/M). We partition the sample at the median by high and low B/M. The second measure is the growth of total assets (*Growth*). The results suggest that the association between trade credit and returns is stronger when the firm is a high-growth firm.

3.5 Trade credit and future fundamentals

The return predictability of trade credit should be supported by its association with future fundamentals. Thus, we directly examine whether trade credit can predict buyers' future accounting performance. To measure accounting performance, we use changes in earnings and revenue, as well as changes in accounts payables and inventory, because they are directly affected by the expansion of trade credit. Since accounting data are released quarterly, we test the relation between monthly trade credit and the upcoming quarter's accounting news using the following equation:

$$Y_{i,q} = \alpha + \beta_1 \Delta OnTime_{i,m1} + \beta_2 \Delta OnTime_{i,m2} + \beta_3 \Delta OnTime_{i,m3} + \beta_4 Y_{i,\,q-4} + \varepsilon_{i,q} \qquad (1)$$

where Y is one of the four accounting variables: seasonal changes in earnings ($\Delta Earn$), seasonal changes in revenue ($\Delta Sales$), seasonal changes in accounts payables (ΔAP), and seasonal changes in inventory (ΔINV). The variables of interest are changes in on-time trade credit measured at the end of the first, second, and third months of quarter q. We predict positive β_1, β_2, and β_3 given the positive association between trade credit and stock returns. We include Y_{q-4} to control for the serial correlation in accounting variables. Note that the trade credit in all three months are measured before the release of quarterly accounting data, which typically occurs several weeks after the end of the quarter.

Table 7 presents the results from the estimation of Equation (1) for the major suppliers. The results presented in Panels A and B show that the change in trade credit is positively correlated with changes in accounts payables, inventory, earnings and revenues. These findings are consistent with the results of the positive association between trade credit and stock returns shown in Tables 3–6. The results suggest that the major suppliers have private information about their buyers.

3.6 Minor suppliers

Our results focus on the major supplier since major suppliers have more incentives to monitor their buyers, and because of data limitations. In this section, we turn our attention to the minor suppliers. These suppliers have, perhaps, less incentives to monitor their buyers. However, we aim to see whether they also possess private information about their buyers. Untabulated tests of the association between minor supplier trade credit and future abnormal returns provide weaker results. For example, the relationship between the percentage of past due trade credit of the minor suppliers and future abnormal returns is only statistically different than zero when dropping the years of the financial crisis. Thus, we test the association between the change in the trade credit of minor suppliers and future accounting performance.

Table 8 presents the results of estimating Equation (1) using the information from the trade credit of minor suppliers. The results show that the monthly change in trade credit of minor suppliers is positively correlated with changes in accounts payables, inventory, earnings, and revenues. These findings are similar to the results of the analysis of the trade credit of major suppliers. The results suggest that, similar to major suppliers, minor suppliers also possess private information about their buyers.

4. CONCLUSION

Despite the importance of trade credit for business-to-business contracting, there is little direct evidence as to whether suppliers have private information about their buyers. In this paper, we provide direct tests of the informational content of trade credit offerings between suppliers and their buyers using a proprietary dataset on trade credit decisions made by suppliers.

We find that the change in the amount of trade credit that suppliers are willing to sell to their buyers is associated with future abnormal stock returns. We further find that the ability of the buyer to pay suppliers on time is also associated with future abnormal stock returns. We also provide evidence based on moderating variables which further support the interpretation that this return predictability reflects private information. Finally, we find that the change in monthly trade credit is positively correlated with changes in the upcoming quarter's accounts payables, inventory, earnings, and revenues. To our knowledge, these findings provide the first large-sample evidence on whether suppliers of trade credit have private information about their customers.

Appendix: Variable Definitions[12]

Variable Names	Definition
TradeCredit	Amount of total trade credit received at the end of month t.
OnTime	Amount of on time trade credit at the end of month t.
PastDue	Amount of past due trade credit at the end of month t.
TradeCredit/AT	Total trade credit deflated by the buyer's total assets of the most recent fiscal year.
TradeCredit/AP	Total trade credit deflated by the buyer's accounts payable of the most recent fiscal year.
PastDue%	Percentage of trade credit that is past due.
PastDue30%	Percentage of trade credit that is past due for less than 30 days.
PastDueOver30%	Percentage of trade credit that is past due for more than 30 days.
PastDueOver60%	Percentage of trade credit that is past due for more than 60 days.
PastDueOver90%	Percentage of trade credit that is past due for more than 90 days.
N_Supplier	Number of suppliers offering trade credit to the buyer in month t.
HHI	Supplier Herfindahl–Hirschman index. It is calculated as the sum of squared market shares of all suppliers in month t. The higher HHI, the more concentration in suppliers.
Avg_RelationLength	The average number of months since suppliers started to offer trade credit to the buyer.
Avg_TradeCredit	The average amount of trade credit offered by each supplier in month t.
Major%	Percentage of trade credit that is contributed by the major supplier. The major supplier is the supplier that offers the largest amount of trade credit in month t.
ΔTradeCredit_Major	Changes in the size of the major supplier's trade credit from the same month last year. The major supplier's trade credit is deflated by the buyer's total assets of the most recent fiscal year.

[12] Dollar amounts are in millions.

ΔOnTime_Major	Changes in the size of the major supplier's on-time trade credit from the same month last year. The major supplier's on-time trade credit is deflated by the buyer's total assets of the most recent fiscal year.
PastDue%_Major	Percentage of the major supplier's total trade credit that is past due.
ΔTradeCredit_Minor	Changes in the size of non-major suppliers' trade credit from the same month last year. Non-major suppliers' trade credit is deflated by the buyer's total assets of the most recent fiscal year.
ΔOnTime_Minor	Changes in the size of non-major suppliers' on-time trade credit from the same month last year. Non-major suppliers' on-time trade credit is deflated by the buyer's total assets of the most recent fiscal year.
PastDue%_Minor	Percentage of non-major suppliers' total trade credit that is past due.
AT	Buyer's total assets of the most recent fiscal year.
AP	Buyer's accounts payable of the most recent fiscal year.
MVE	Buyer's market value of equity at the end of month t.
Ret	Buyer's monthly stock return in month $t+1$.
Cash Ratio	Buyer's cash ratio of the most recent fiscal year. Cash ratio = (cash + short-term investments)/ current liabilities.
CFO/CL	Buyer's cash flow from operations divided by average current liabilities in the most recent fiscal year.
Leverage	Buyer's leverage ratio of the most recent fiscal year. Leverage = total liabilities / total assets.
Distress	An indicator variable of high default risk of the buyer based on Altman Z-score. Distress = 1 if Z-score < 1.8, 0.5 if 1.8 <= Z-score <= 2.99, and 0 if Z-score > 2.99.
B/M	Buyer's book-to-market ratio as of the most recent fiscal year end.
Growth	Buyer's growth of total assets in the most recent fiscal year. Growth of total assets = (ending total assets - beginning total assets) / beginning total assets.

ΔEarn	Seasonal changes in income before extraordinary items (IB) for quarter *q*, calculated as (IB of quarter *q* - IB of quarter *q-4*)/ market value of equity at the end of quarter *q*.
ΔSales	Seasonal changes in sales for quarter *q*, calculated as (sales of quarter *q* - sales of quarter *q-4*)/ market value of equity at the end of quarter *q*.
ΔAP	Seasonal changes in accounts payables for quarter *q*, calculated as (AP of quarter *q* - AP of quarter *q-4*)/ market value of equity at the end of quarter *q*.
ΔINV	Seasonal changes in inventory for quarter *q*, calculated as (inventory of quarter *q* - inventory of quarter *q-4*)/ market value of equity at the end of quarter *q*.

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Table 1 – Sample Description

Panel A: Sample Selection

		# of Buyer-months	# of Distinct Buyers	# of Supplier-Buyer Pair months	# of Distinct Supplier-Buyer Pairs
	All Obs	2,342,262	32,749	14,642,580	502,847
minus:	Obs not traded in the three major exchanges	(1,824,107)	(26,497)	(9,201,163)	(315,930)
minus:	Obs without monthly stock returns	(3,850)	(65)	(23,588)	(707)
minus:	Obs without valid financial data from the most recent fiscal year	(7,939)	(173)	(24,152)	(1,277)
minus:	Obs without sufficient data to calculate changes in trade credit	(83,775)	(736)	(204,565)	(6,537)
	Final Sample	**422,591**	**5,278**	**5,189,112**	**178,396**

Panel B: Sample Distribution by Year

Year	# of Buyer-months	# of Distinct Buyers	# of Distinct Supplier-Buyer Pairs
2002	2,975	1,012	4,627
2003	15,463	1,944	9,792
2004	19,748	2,172	11,031
2005	20,962	2,301	12,825
2006	22,960	2,477	22,307
2007	26,117	2,748	27,460
2008	28,730	2,790	37,266
2009	30,203	2,933	47,236
2010	31,268	2,965	46,617
2011	30,614	2,897	51,175
2012	31,138	2,915	56,964
2013	32,741	3,071	64,997
2014	33,333	3,095	69,792
2015	33,835	3,191	74,756
2016	33,174	3,145	79,460
2017	29,330	2,968	75,373
Total	**422,591**		

Panel C: Sample Distribution by Industry

Industry Name	# of Buyer-months	Distinct Buyers		Distinct Firms in the Stock Universe	
		#	%	#	%
Consumer NonDurables	25,172	246	4.7%	371	4.1%
Consumer Durables	13,047	116	2.2%	193	2.1%
Manufacturing	54,195	500	9.5%	725	8.1%
Oil, Gas, and Coal Extraction and Products	18,450	222	4.2%	364	4.0%
Chemicals and Allied Products	13,117	131	2.5%	180	2.0%
Business Equipment	76,077	1,067	20.2%	1898	21.1%
Telephone and Television Transmission	10,822	143	2.7%	259	2.9%
Utilities	13,754	119	2.3%	144	1.6%
Wholesale, Retail, and Some Services	49,611	518	9.8%	718	8.0%
Healthcare, Medical Equipment, and Drugs	46,077	756	14.3%	1263	14.0%
Finance	49,239	846	16.0%	1751	19.5%
Other	53,030	614	11.6%	1132	12.6%
Total	**422,591**	**5,278**		**8,998**	

This table describes sample selection and distribution. Panel A reports the sample selection process. Panel B reports distribution of the sample over years. Panel C reports distribution of the sample over 12 Fama-French industries. 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 ($m)	422,591	6.091	0.174	48.516	0.018	1.411
OnTime	422,591	5.092	0.115	43.537	0.010	1.034
PastDue	422,591	0.999	0.032	7.458	0.002	0.278
TradeCredit/AT	422,591	0.15%	0.02%	0.66%	0.00%	0.10%
TradeCredit/AP	418,471	2.23%	0.43%	11.52%	0.06%	1.78%
PastDue%	410,098	27.23%	19.82%	26.44%	6.51%	39.53%
PastDue30%	410,098	17.80%	11.58%	20.55%	2.43%	25.00%
PastDueOver30%	410,098	9.43%	2.27%	18.18%	0.02%	9.28%
PastDueOver60%	410,098	5.16%	0.55%	14.00%	0.00%	3.35%
PastDueOver90%	410,098	3.08%	0.08%	11.13%	0.00%	1.29%
N_Supplier	422,591	12.28	6.00	16.18	3.00	15.00
HHI	410,098	57.73%	52.94%	29.61%	32.13%	88.23%
Avg_RelationLength (month)	422,591	33.33	30.67	17.70	20.00	45.00
Avg_TradeCredit ($m)	422,591	0.196	0.027	0.909	0.005	0.113
Major%	410,098	67.72%	68.23%	25.47%	46.43%	93.79%
⊿TradeCredit_Major	422,591	0.0078%	0.0001%	0.4792%	-0.0050%	0.0088%
⊿OnTime_Major	422,591	0.0054%	0.0000%	0.3719%	-0.0035%	0.0064%
PastDue%_Major	410,098	26.41%	12.56%	32.01%	0.00%	43.40%
⊿TradeCredit_Minor	422,591	0.0080%	0.0000%	0.1080%	-0.0006%	0.0056%
⊿OnTime_Minor	422,591	0.0063%	0.0000%	0.0933%	-0.0004%	0.0039%
PastDue%_Minor	350,131	28.34%	22.10%	25.68%	8.90%	40.25%

Panel B – Accounting and Financial Information

	N	Mean	Median	StdDev	Q1	Q3
AT ($m)	422,591	11898	1020	82221	271	4144
AP	419,246	3107	55	37751	12	276
MVE	422,591	6471	953	23905	244	3554
Ret	422,591	1.28%	0.83%	14.32%	-5.13%	6.83%
Cash Ratio	374,999	1.186	0.500	2.207	0.165	1.262
CFO/CL	373,571	0.465	0.460	1.028	0.188	0.810
Leverage	421,620	0.549	0.537	0.279	0.356	0.712
Distress	422,591	0.421	0.500	0.443	0.000	1.000
B/M	422,244	0.574	0.479	31.889	0.274	0.760
Growth	421,329	0.134	0.051	1.055	-0.025	0.154
∆Earn	127,996	-0.65%	0.11%	59.89%	-0.55%	0.63%
∆Sales	127,996	-0.51%	0.79%	44.27%	-0.67%	2.84%
∆AP	126,776	1.37%	0.22%	47.01%	-0.48%	1.42%
∆INV	124,733	-0.43%	0.02%	32.27%	-0.24%	1.15%

This table reports descriptive statistics for the full sample. Panel A reports the descriptive of the trade credit information. Panel B reports accounting and financial information. Except for *∆Earn, ∆Sales, ∆AP* and *∆INV* which are at buyer-quarter level, all variables are at buyer-month level. Variable definitions are available in the appendix.

Table 3 – On Time Trade Credit and Stock Returns

		(1) Portfolio L	(2) 2	(3) 3	(4) 4	(5) H	(6) **H-L**
All Firms							
CAPM	alpha	-0.09	0.01	-0.14	0.02	0.29	**0.37**
	t	(-0.70)	(0.07)	(-1.17)	(0.24)	(2.69)***	**(2.25)****
Carhart4	alpha	-0.09	0.02	-0.11	0.00	0.25	**0.34**
	t	(-0.75)	(0.21)	(-0.99)	(-0.04)	(2.55)**	**(2.10)****
FF5	alpha	-0.18	-0.05	-0.05	-0.02	0.25	**0.43**
	t	(-1.54)	(-0.45)	(-0.45)	(-0.20)	(2.34)**	**(2.52)****
All but Micro							
CAPM	alpha	-0.07	-0.01	-0.19	0.07	0.26	**0.33**
	t	(-0.56)	(-0.14)	(-1.61)	(0.78)	(2.59)**	**(2.02)****
Carhart4	alpha	-0.07	0.00	-0.17	0.05	0.22	**0.30**
	t	(-0.65)	(0.00)	(-1.46)	(0.54)	(2.43)**	**(1.88)***
FF5	alpha	-0.17	-0.06	-0.10	0.03	0.21	**0.39**
	t	(-1.52)	(-0.58)	(-0.84)	(0.34)	(2.16)**	**(2.31)****

This table reports the average value weighted abnormal returns of 5 portfolios one-way sorted on $\Delta OnTime\_Major$. Alpha is the monthly portfolio average abnormal return, obtained as the intercept from monthly CAPM, Carhart (1997) or Fama-French (2015) regressions. H-L stands for the High minus Low $\Delta OnTime\_Major$ portfolio. The table reports results for all the firms in the sample (All Firms) and across a subsample of firms that excludes micro cap firms (All but Micro), defined as the firms with market value below $300 million at the end of the previous month. The sample includes 186 months from June 2002 to November 2017. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4 – Past Due Trade Credit and Stock Returns

		(1) L	(2) 2	(3) 3	(4) 4	(5) H	(6) **H-L**
<u>All Firms</u>							
CAPM	alpha	0.26	0.01	0.02	-0.03	-0.01	**-0.32**
	t	(2.50)**	(0.06)	(0.28)	(-0.33)	(-0.12)	**(-2.56)****
Carhart4	alpha	0.25	-0.01	0.01	-0.03	-0.02	**-0.32**
	t	(2.48)**	(-0.04)	(0.08)	(-0.39)	(-0.22)	**(-2.60)****
FF5	alpha	0.19	-0.05	0.00	-0.11	-0.08	**-0.30**
	t	(1.80)*	(-0.38)	(0.03)	(-1.45)	(-0.68)	**(-2.32)****
<u>All but Micro</u>							
CAPM	alpha	0.25	-0.02	0.09	-0.06	-0.05	**-0.34**
	t	(2.43)**	(-0.15)	(0.95)	(-0.80)	(-0.48)	**(-2.79)*****
Carhart4	alpha	0.25	-0.04	0.07	-0.06	-0.05	**-0.34**
	t	(2.39)**	(-0.35)	(0.81)	(-0.78)	(-0.53)	**(-2.78)*****
FF5	alpha	0.19	-0.10	0.00	-0.11	-0.09	**-0.31**
	t	(1.75)*	(-0.81)	(0.04)	(-1.27)	(-0.92)	**(-2.44)****

This table reports the average value weighted abnormal returns of 5 portfolios one-way sorted on *PastDue%_Major*. Alpha is the monthly portfolio average abnormal return, obtained as the intercept from monthly CAPM, Carhart (1997) or Fama-French (2015) regressions. H-L stands for the High minus Low *PastDue%_Major* portfolio. The table reports results for all the firms in the sample (All Firms) and across a subsample of firms that excludes micro cap firms (All but Micro), defined as the firms with market value below $300 million at the end of the previous month. The sample includes 186 months from June 2002 to November 2017. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5 – Trade Credit and Stock Returns: No Financial Crisis

		(1) L	(2) 2	(3) 3	(4) 4	(5) H	(6) **H-L**
On Time							
CAPM	alpha	-0.14	-0.04	-0.08	-0.03	0.30	**0.44**
	t	(-1.08)	(-0.31)	(-0.57)	(-0.35)	(2.43)**	**(2.40)****
Carhart4	alpha	-0.13	-0.02	-0.08	-0.07	0.28	**0.40**
	t	(-1.00)	(-0.20)	(-0.58)	(-0.74)	(2.31)**	**(2.20)****
FF5	alpha	-0.20	-0.06	-0.06	-0.08	0.27	**0.48**
	t	(-1.62)	(-0.49)	(-0.46)	(-0.84)	(2.26)**	**(2.56)****
Past Due							
CAPM	alpha	0.27	0.03	0.05	0.02	-0.09	**-0.44**
	t	(2.34)**	(0.19)	(0.68)	(0.21)	(-0.79)	**(-3.45)*****
Carhart4	alpha	0.24	-0.03	0.00	-0.02	-0.14	**-0.43**
	t	(2.00)**	(-0.23)	(-0.03)	(-0.20)	(-1.18)	**(-3.28)*****
FF5	alpha	0.17	-0.04	-0.01	-0.09	-0.15	**-0.37**
	t	(1.40)	(-0.27)	(-0.14)	(-1.10)	(-1.18)	**(-2.74)*****

This table reports the average value weighted abnormal returns of 5 portfolios one-way sorted on *ΔOnTime_Major*, and *PastDue%_Major*. Alpha is the monthly portfolio average abnormal return, obtained as the intercept from monthly CAPM, Carhart (1997) or Fama-French (2015) regressions. H-L stands for the High minus Low portfolio. The sample is from 2002 to 2017 and excludes the financial crisis (years 2007-2009). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6 – Trade Credit and Stock Returns: Cross Sectional Analysis

Panel A – Supplier Concentration

	HHI		*Major%*
Low *HHI*	0.15	Low *Major%*	0.06
	(0.76)		(0.31)
High *HHI*	0.95	High *Major%*	0.95
	(4.05)***		(4.04)***

Panel B – Short Term Liquidity

	Cash Ratio		*CFO/CL*
Low *Cash Ratio*	0.00	Low *CFO/CL*	0.03
	(0.00)		(0.16)
High *Cash Ratio*	0.72	High *CFO/CL*	0.54
	(2.98)***		(2.46)**

Panel C – Long Term Liquidity

	Leverage		*Distress*
Low *Leverage*	0.54	Low *Distress*	0.49
	(2.30)**		(2.38)**
High *Leverage*	0.17	High *Distress*	0.12
	(1.10)		(0.60)

Panel D - Growth

	B/M		*Growth*
Low *B/M*	0.50	Low *Growth*	0.11
	(2.69)***		(0.68)
High *B/M*	0.11	High *Growth*	0.49
	(0.57)		(2.23)**

This table reports the Fama-French (2015) alphas on a monthly hedging portfolio based on *△OnTime_Major* for various subsamples. Subsamples are divided by the median for each month. *HHI* is the sum of suppliers' squared market shares of trade credit in month *t*. *Major%* is the percentage of trade credit contributed by the major supplier. *Cash Ratio* is the buyer's cash plus short-term investments deflated by current liabilities. *CFO/CL* is the buyer's operating cash flows to current liabilities ratio. *Leverage* is total liabilities deflated by total assets. *Distress* is an indicator variable that receives the value of one for high-default risk based on the Altman (1968) Z-score. *B/M* is the book-to-market ratio. *Growth* is the annual growth of total assets. All financial variables are measured at the most recent fiscal year end. The table reports results for all the firms in the sample (All Firms). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7 – Major Supplier and Future Performance

Panel A – Accounts Payables and Inventory

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Y =		ΔAP				ΔINV		
1st Month *⊿OnTime_Major*	0.180%			-0.012%	0.394%			0.199%
	(3.30)***			(-0.18)	(9.34)***			(4.50)***
2nd Month *⊿OnTime_Major*		0.345%		0.191%		0.416%		0.216%
		(6.37)***		(2.99)***		(9.63)***		(4.58)***
3rd Month *⊿OnTime_Major*			0.374%	0.329%			0.429%	0.273%
			(6.80)***	(5.29)***			(9.56)***	(5.62)***
Y in q-4	0.799	0.800	0.798	0.793	0.735	0.731	0.733	0.736
	(109.35)***	(110.27)***	(109.04)***	(98.45)***	(92.11)***	(92.11)***	(96.06)***	(93.05)***
Constant	0.003	0.002	0.002	0.001	-0.002	-0.002	-0.002	-0.003
	(7.80)***	(5.60)***	(5.08)***	(2.15)**	(-7.15)***	(-7.32)***	(-7.60)***	(-9.69)***
N	136,215	137,971	136,830	126,695	133,579	135,299	134,194	124,201
Adjusted R-squared	0.639	0.643	0.643	0.632	0.536	0.533	0.537	0.539

Panel B – Earnings and Revenues

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Y =		Δ*Earn*				Δ*Sales*		
1st Month Δ*OnTime_Major*	0.231%			0.092%	0.539%			0.176%
	(4.17)***			(1.44)	(7.84)***			(2.29)**
2nd Month Δ*OnTime_Major*		0.293%		0.143%		0.735%		0.486%
		(5.30)***		(2.18)**		(10.22)***		(5.98)***
3rd Month Δ*OnTime_Major*			0.318%	0.247%			0.680%	0.471%
			(5.65)***	(3.85)***			(9.24)***	(5.84)***
Y in q-4	0.235	0.231	0.226	0.229	0.712	0.706	0.706	0.711
	(25.41)***	(25.43)***	(25.44)***	(24.50)***	(115.92)***	(115.22)***	(116.38)***	(115.45)***
Constant	-0.003	-0.003	-0.003	-0.004	-0.002	-0.003	-0.003	-0.006
	(-8.18)***	(-9.17)***	(-9.43)***	(-9.86)***	(-5.96)***	(-7.83)***	(-7.18)***	(-10.22)***
N	137,660	139,427	138,265	127,996	137,660	139,427	138,265	127,996
Adjusted R-squared	0.050	0.049	0.048	0.049	0.492	0.488	0.488	0.495

This table reports the results of estimating equation (1) for the major suppliers. The dependent variable Δ*Earn* (Δ*Sales*, Δ*AP*, *or* Δ*INV*) is the seasonal change in income before extraordinary items (revenues, accounts payable, inventory) for quarter *q*. Δ*OnTime_Major* at the end of the 1st, 2nd, and 3rd month of quarter *q* are sorted into quintiles and bounded to [0, 1]. Standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8 – Minor Supplier and Future Performance

Panel A - Accounts Payables and Inventory

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Y =		ΔAP				ΔINV		
1st Month $\Delta OnTime\_Minor$	0.066%			-0.171%	0.455%			0.232%
	(1.29)			(-3.02)***	(10.55)***			(4.74)***
2nd Month $\Delta OnTime\_Minor$		0.202%		0.082%		0.455%		0.151%
		(3.88)***		(1.35)		(10.21)***		(2.95)***
3rd Month $\Delta OnTime\_Minor$			0.399%	0.447%			0.557%	0.396%
			(7.47)***	(7.49)***			(11.97)***	(7.85)***
Y in q-4	0.772	0.771	0.770	0.770	0.747	0.744	0.746	0.747
	(90.13)***	(91.00)***	(89.74)***	(86.72)***	(95.76)***	(96.41)***	(99.07)***	(97.22)***
Constant	0.002	0.001	0.000	0.001	-0.002	-0.002	-0.003	-0.004
	(5.53)***	(3.78)***	(1.09)	(1.14)	(-8.49)***	(-8.13)***	(-9.85)***	(-11.61)***
N	114,556	115,342	113,941	110,689	112,169	112,950	111,579	108,388
Adjusted R-squared	0.586	0.587	0.588	0.587	0.547	0.547	0.551	0.551

Panel B – Earnings and Revenues

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Y =		Δ*Earn*				Δ*Sales*		
1st Month *ΔOnTime_Minor*	0.304%			0.154%	0.578%			0.188%
	(5.19)***			(2.27)**	(7.53)***			(2.19)**
2nd Month *ΔOnTime_Minor*		0.320%		0.140%		0.773%		0.472%
		(5.52)***		(2.06)**		(9.55)***		(5.19)***
3rd Month *ΔOnTime_Minor*			0.360%	0.245%			0.771%	0.511%
			(6.10)***	(3.69)***			(9.34)***	(5.79)***
Y in q-4	0.241	0.238	0.235	0.235	0.721	0.718	0.717	0.719
	(24.39)***	(24.59)***	(24.52)***	(24.07)***	(109.84)***	(110.97)***	(111.59)***	(110.33)***
Constant	-0.003	-0.003	-0.003	-0.004	-0.003	-0.004	-0.004	-0.006
	(-9.69)***	(-9.89)***	(-10.47)***	(-10.72)***	(-6.20)***	(-7.79)***	(-7.70)***	(-9.75)***
N	115,706	116,493	115,073	111,784	115,706	116,493	115,073	111,784
Adjusted R-squared	0.053	0.052	0.051	0.052	0.502	0.500	0.500	0.502

This table reports the results of estimating equation (1) for the minor suppliers. The dependent variable *ΔEarn* (*ΔSales, ΔAP, or ΔINV*) is the seasonal change in income before extraordinary items (revenues, accounts payable, inventory) for quarter *q*. *ΔOnTime_Minor* at the end of the 1st, 2nd, and 3rd month of quarter *q* are sorted into quintiles and bounded to [0, 1]. Standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.