Review of Quantitative Finance and Accounting (2022) 58:1363–1394
https://doi.org/10.1007/s11156-021-01027-7

ORIGINAL RESEARCH

Capturing the straw in the wind: do short sellers trade on customer information?

In-Mu Haw[1] · Wenming Wang[2] · Wenlan Zhang[3] · Xu Zhang[4]

Accepted: 11 November 2021 / Published online: 4 January 2022

Abstract
This study investigates whether short sellers trade the stocks of suppliers on customer information. Using the daily short-selling data derived from the Trades and Quotes-Regulation SHO database, we find that short sellers exploit the earnings news of major customers to trade the supplier stocks. Our cross-sectional tests show that short sellers' trading on customer information is reduced when the suppliers and customers have common analysts or a higher percentage of common transient institutional investors, and is exacerbated for supplier–customer pairs when the supplier is more economically linked with the customer or when the short-sale constraint of the supplier is lower. Further analyses indicate that though short sellers' trading on customer information is mainly driven by their superior ability to interpret the public information of the customers, we find some evidence that short sellers trade on private information of the customers. This study identifies the intermediary role of short sellers in incorporating customer-specific information into the supplier's stock price and mitigating the supplier–customer anomaly. It adds to a growing body of studies on information transfer along supply chains.

Keywords Short selling · Supplier–customer relationship · Earnings announcement · Information environment · Public information · Private information

✉ In-Mu Haw
i.haw@tcu.edu

Wenming Wang
wwming@zju.edu.cn

Wenlan Zhang
wenlanzhang@dufe.edu.cn

Xu Zhang
xuzhang@umac.mo

1 Neeley School of Business, Texas Christian University, Fort Worth, TX 76129, USA

2 Department of Finance and Accounting, School of Management, Zhejiang University, Hangzhou 310058, People's Republic of China

3 School of Accounting, Dongbei University of Finance and Economics, Dalian 116025, People's Republic of China

4 Department of Accounting, Faculty of Business Administration, University of Macau, Av. Padre Tomás Pereira, Taipa, Macau

JEL Classification L14 · G14 · G2

1 Introduction

A large body of studies have documented that a firm's value creation is materially affected by the operating behaviors of its major customers, such as financial distresses (Titman 1984; Hertzel et al. 2008; Kolay et al. 2016), financing decisions (Kutsuna et al. 2016), horizontal mergers and acquisitions (Bhattacharyya and Nain 2011), and financial reporting misconducts (Kang et al. 2012). These studies suggest that the information of major customers could be useful to investors for valuing supplier firms. Our study focuses on the earnings news of customers and investigates the short selling of supplier's stock based on customer information.[1]

Researchers have found evidence that investors take the information of major customers into account upon making trading decisions on supplier firms (e.g., Hertzel et al. 2008; Pandit et al. 2011; Madsen 2017). However, the extant literature largely infers indirectly from the stock price reactions of supplier firms to their major customers' news due to the detailed trading data limitation. Relying on the daily short-selling data derived from the TAQ-RegSHO database, the first objective of this study is to provide direct and robust evidence on whether investors, short-sellers in particular, exploit major customers' information in trading supplier stocks.

Short sellers have long been recognized as well-informed and sophisticated investors (e.g., Christophe et al. 2004; Desai et al. 2006; Engelberg et al. 2012; Khan and Lu 2013; Lee 2016; Choy and Zhang 2019). Prior studies have suggested that the information advantage of short sellers could be derived from either private information or their sophisticated skills in interpreting public information. Short sellers have exceptional skills in collecting and processing the relevant information of a firm so that they can profit by taking a short position on overvalued stocks. Cohen and Frazzini (2008) find that the stock prices of supplier firms adjust with a lag to the news of their major customers, generating return predictability (i.e., customer–supplier anomaly). The customer–supplier anomaly offers short sellers the opportunity to profit from trading the supplier stocks.

Short sellers tend to target firms with higher information asymmetry (Desai et al. 2006; Khan and Lu 2013). Prior studies have identified several forces that can promote the information transfer along the supply chain and mitigate the customer–supplier anomaly. Specifically, Cohen and Frazzini (2008) document that institutional investors that own both the customer and the supplier are more attentive to the customer–supplier link and reduce the customer–supplier anomaly. Luo and Nagarajan (2015) reveal that supply chain analysts,

[1] On average, suppliers are substantially smaller than customers and highly dependent on their customers (e.g., Cheung et al. 2020; Fee et al. 2006). Cheung et al. (2020) report that the median value of total assets ($ in million) is $178 for suppliers and $5572 for customers, and the median sales dependence of suppliers on customers is 15% and the median cost dependence of customers on suppliers is 0.2%. Hence, the supplier's information is likely to have little material value for short sellers to trade customer stock, whereas customer information should be more valuable to investors and more likely to attract the attention of short sellers. Furthermore, current accounting standards in the U.S. (SFAS 14 and SFAS 131) require public firms to disclose major customers (greater than 10% of sales), but not major suppliers. Therefore, we can directly identify a firm's all major customers but cannot identify a firm's all major suppliers. SFAS 14 and 39 stipulate that "if 10% or more of the revenue of an enterprise is derived from sales to any single customer, that fact and the amount of revenue from each such customer shall be disclosed.".

who simultaneously follow both suppliers and customers, are better able to incorporate customer-specific information in generating earnings forecasts for the supplier firms and improve the efficiency of supplier firms' valuations. Following this line of inquiry, the second objective of this study is to examine whether short sellers' trading on customer news is reduced when the supply chains share the same analysts or the common institutional investors.

Customer information can be more valuable to investors and more likely to attract the attention of short sellers when suppliers are highly dependent on their customers or have a longer relationship with their customers (e.g., Pfeffer and Salancik 1978). Thus, the third objective of this study is to examine whether short sellers' trading on customer news is more pronounced for supplier–customer pairs with stronger economic ties.

We utilize the short-selling data of the TAQ-RegSHO database from January 3, 2005 to July 6, 2007 and the supplier–customer information from the COMPUSTAT segment files to construct a sample of 2643 supplier–customer-quarterly observations. We focus on the short selling activities of supplier stocks around the quarterly earnings announcements (QEA) of their major customers. Our results reveal that the cumulative abnormal volume of short-sales (*CAVSS*) of the supplier stocks during an event window of [− 10, 10] days is significantly higher when a major customer reports more negative unexpected earnings. The results suggest that short sellers exploit the information pertinent to major customers in their trading decisions of supplier stocks. Our findings are robust to various alternative event windows, an alternative measure of short selling volume, the inclusion of supplier–customer pair fixed effects, the control for the effect of overpricing, and consideration of information leakage.

We conduct cross-sectional tests on whether short sellers' trading on the customer-specific information varies with the characteristics of the supplier–customer relationship and information environment. We find that short sellers' trading on customer news is mitigated when the suppliers and their customers have common analysts or a higher percentage of common transient institutional investors,[2] but is exacerbated when the supplier–customer pairs have stronger economic ties measured by higher dependence of the supplier on the customer,[3] or longer duration.

Furthermore, we explore whether short sellers trade on public or private information regarding major customers to identify the underlying channel of the information advantage of short sellers in two ways. First, we focus on the *CAVSS* in the event window of [− 10, − 1] days before and the event window of [0, 10] days after the QEA of the major customers. We observe a significantly negative association between the *CAVSS* and the customers' unexpected earnings for the event window of [0, 10] days, but an insignificant association for the event window of [− 10, − 1] days.[4] Second, we examine the time varying

[2] In this study, we only consider transient institutional investors as previous research has generally confirmed that unlike dedicated institutional investors who are long-term active monitors and quasi-indexers who are passive investors, transient institutional investors provide information through frequent trading (Bushee 1998; Yan and Zhang 2009). We follow Bushee (1998) and label institutional investors as transient, dedicated or quasi-indexing institutional investors.

[3] As shown in Sect. 5.4.2, we measure the dependence of supplier on customer based on the percentage of sales to the customer or product complexity proxied by R&D expenditures over total assets. Firms with R&D expenditures over total assets above the year-quarter median in the quarter before the earnings announcement of the customer have high product complexity.

[4] We obtain similar results with various alternative event windows including [0, 5], [− 5, − 1], [0, 3] and [− 3, − 1] days, respectively. Alternatively, we restrict our sample to the QEA of customers in the *first year* of the customer–supplier relationship, which likely precedes the public disclosure of the relationship to the

effect of the association between the *daily* abnormal short-sale volume of the supplier firm and the standardized unexpected earnings (SUE) of the customers across an event window of [− 10, 10] days. On average, we find insignificant associations on days before earnings announcements, and significantly negative association on day 0, 3, 4, 6, 7 and 8 after the earnings announcement, suggesting continuous short selling activities. We further explore the circumstances where short sellers trade on private information of customers, and find short sellers' significant abnormal trading of supplier stocks on days -4 and -5 before earnings announcements when the supplier–customer pairs do not share the same analysts or have fewer common transient institutional investors. Taken together, our results suggest that though the abnormal short selling activities of supplier stocks are largely driven by the public information of major customers, short sellers also trade on customer private information in the circumstances where investors of suppliers are inattentive to customer information.

We conduct several additional analyses to strengthen the validity of our findings. First, we test how short-sale constraints of suppliers (proxied by institutional ownership and an indicator of stocks exempted from uptick tests) affect our analysis and find that our results are more pronounced for supplier–customer pairs when the short-sale constraints of suppliers are lower. Second, following Israeli et al. (2017), we decompose the unexpected earnings of customers into macro-based component and firm-specific component and find that short sellers mainly trade on the firm-specific earnings information of customers. Third, we test and find that the customer's unexpected earnings indeed predict the supplier's future operating performance, suggesting that short selling on customer earnings information can be profitable. Finally, we assess the economic consequence of short sellers' trading on the customer-specific information by testing whether short sellers' trading increases the incorporation of customer information into the supplier's stock prices. Our results show that the contemporary association between customer and supplier stock returns is significantly positive for the supplier–customer pairs with higher short-sale volume of supplier stocks and negative customer unexpected earnings. It suggests that short sellers promote the timely incorporation of customer information into the supplier's stock prices and enhance the stock price efficiency for the suppliers.

Our study contributes to the literature in several ways. First, it adds to a growing body of studies on information transfer along supply chains (e.g., Hertzel et al. 2008; Pandit et al. 2011; Madsen 2017). Prior studies infer that market participants such as equity investors take major customers' information into account when making decisions about supplier firms (Hertzel et al. 2008; Pandit et al. 2011; Guan et al. 2015; Kim et al. 2015; Luo and Nagarajan 2015; Gong and Luo 2018). We further provide *direct* evidence that investors, short sellers in particular, exploit customer information to trade supplier stocks.

Second, this study contributes to the debate on the underlying channels that provide information advantages to short sellers. Some studies show that short sellers' trading advantages originate from their access to private information (e.g., Christophe et al. 2004, 2010; Karpoff and Lou 2010; Massoud et al. 2011; Khan and Lu 2013), while others attribute short sellers' trading advantages to their superior ability to interpret public information (e.g., Dechow et al. 2001; Engelberg et al. 2012). We focus on information environments along supply chains (i.e., common analysts and common transient

Footnote 4 (continued)

market (Alldredge and Cicero 2015). We do not find any negative association between the *CAVSS* and the unexpected earnings of the customers in this subsample.

institutional investors) and find evidence supporting both arguments. On the one hand, we observe an abnormally high short-sale volume of supplier stocks immediately after the negative earnings announcement by major customers, indicating that the trading advantages of short sellers are largely derived from their superior ability to process public information. On the other hand, we find that short sellers trade on private information of customers when suppliers' investors are inattentive to customer information, supporting short sellers' access to firm private information.

Third, our study contributes to the literature on the customer–supplier anomaly. Since Cohen and Frazzini (2008) identify the customer–supplier anomaly, several studies have explored the determinants of this anomaly (e.g., Pandit et al. 2011) and identify various factors that mitigate this anomaly (Luo and Nagarajan 2015; Madsen 2017). Our study further uncovers that an important type of investors, namely short sellers, can accelerate the flow of information along supply chains and mitigate the customer–supplier anomaly.

In a concurrent study, Dai et al. (2017) examine whether short sellers trade on news of related firms and find that short sellers trade on public customer news. Our study is distinct from Dai et al. (2017) in four important ways. First, Dai et al. (2017) explore the relationship between abnormal short selling of supplier stocks and post-news customer stock returns; we examine the relationship between abnormal short-sale of supplier stocks around the quarterly earnings announcements of their major customers and the standardized unexpected earnings of the customers. The post-news customer returns in their study capture not only the news specific to the focal customers but also contemporaneous market-wide or industry-related news. In contrast, our use of the unexpected earnings of the customers can rule out the confounding effect of potential non-customer-specific events, which enables our research design to more directly test the research question about information transfer along supply chains.

Second, both Dai et al. (2017) and our study explore the moderating factors of information transfer but analyze different characteristics and information environments. Dai et al. (2017) focus on the information asymmetry of suppliers, i.e., the media coverage, institutional owners and analyst coverage of suppliers. In contrast, we focus on the *features of supply chains*, i.e., common analyst, common transient institutional investors, and the economic ties between a supplier and its major customer.

Third, both Dai et al. (2017) and our study explore the information sources of short sellers in trading decisions and find that short sellers trade on public information of customers. Moreover, by taking the information environments of supply chains into consideration, our granular analyses further reveal that short sellers trade on private information of customers when the suppliers' investors are inattentive to customer information as well.

Finally, we explore two additional research questions over and beyond Dai et al. (2017), which are related to the economic consequence of short selling and the effect of short-sale constraints of suppliers on customer information. We find that short selling on customer information promotes the incorporation of customer information into supplier stock price, especially when customer information is negative, and that short-sale constraints of suppliers reduce short sellers' trading on customer information.

The remainder of this paper proceeds as follows. Section 2 reviews the literature and develops hypotheses. Section 3 describes the data. Section 4 presents the research design. Section 5 reports the main findings and additional results. Section 6 explores the economic consequence of the trading strategy of short sellers based on customer information, and Sect. 7 concludes.

2 Literature review and hypothesis development

Extant literature shows that customer information can predict its suppliers' performance. Any shock to a major customer firm will have a resulting effect on the performance of its suppliers. For example, the supplier firms experience high replacement costs (Titman 1984; Kolay et al. 2016), and suffer wealth loss at bankruptcy filings by their major customers (Hertzel et al. 2008). Many other events including earnings announcements, financial restatements, horizontal merger and acquisition, and initial public offerings of major customers exert spillover effect on supplier firm's performance as well (Bhattacharyya and Nain 2011; Pandit et al. 2011; Kang et al. 2012; Kutsuna et al. 2016). The interplay and information complementarities between suppliers and customers along a supply chain network can thus be exploited by a variety of market participants for decision making pertaining to supplier firms that includes analyst earnings forecasts (Luo and Nagarajan 2015), loan contracting (Kim et al. 2015), and insider trading (Alldredge and Cicero 2015).

Although customer information is essential for investors to predict supplier performance, previous studies have found that investors underreact to customer information. In particular, Cohen and Frazzini (2008) find stock prices of supplier firms do not promptly incorporate news about their customers, generating predictable subsequent price moves. Chen et al. (2016) find similar results in the bond market. This customer–supplier anomaly can provide short sellers with opportunities to exploit market underreaction to negative customer information and make profitable trades.

Extant literature has shown that short sellers are informed traders. Christophe et al. (2004) uncover a significantly negative relationship between unusual levels of short-selling in the days before the earnings announcement and the immediate post-announcement change in stock prices, providing evidence of informed short-selling. Khan and Lu (2013) take advantage of high-frequency short sales data and find significant increases in short sales immediately prior to large insider sales, suggesting information leakage to short sellers. Compared with general investors, short sellers also have superior ability to collect and process valuation relevant information. Asquith and Meulbroek (1995) find that short sellers can identify the overpriced stocks and thus make a profit by short selling. Dechow et al. (2001) show that short sellers can better interpret a firm's fundamental ratios and accordingly take profitable trading strategies. Desai et al. (2006) provide evidence that short sellers are better able to see through a firm's accrual quality and identify questionable accounting practices than other market participants including analysts and auditors.

In sum, given the evidence on the return predictability of customer information together with the superior ability of short sellers to obtain and process information, we predict that short sellers tend to be active in trading the stocks of suppliers around earnings announcements by their major customers.[5] To be specific, short sellers are expected to increase (decrease) their short positions in the stocks of supplier firms if announced customer information is negative (positive). Thus, we make the following hypothesis:

[5] We also recognize a possibility that short sellers of suppliers don't exploit the information of customers due to the following reasons. First, short sellers may trade to exploit liquidity rather than information (Von Beschwitz et al. 2017). Second, short sellers may not be attentive to the customer information if they don't hold or short sell the stocks of customers. Third, even though short sellers are attentive to the information of customers, they may not use it due to high cost of short selling.

H1 The short-sale volume of the supplier stocks around the major customer's QEA is negatively associated with the customer's unexpected earnings

Cohen and Frazzini (2008) document that the return predictability of customer information can be attributed to the limited attention of supplier investors. Madsen (2017) finds that the anticipation of supplier earnings announcement can, to some extent, resolve investor limited attention to customer information and mitigate returns to the customer–supplier anomaly. An interesting research question is whether varying inattention to the supplier–customer relationships affects short sellers' trading on customer information.

Menzly and Ozbas (2010) show that the return predictability of customer information declines with the levels of analyst coverage and institutional ownership. Many other researchers provide further evidence that common analysts and common institutional investors along the supply chain promote the incorporation of customer information into the stock prices of suppliers and mitigate the supplier–customer anomaly (Cohen and Frazzini 2008; Guan et al. 2015; Luo and Nagarajan 2015; Cen et al. 2017). In other words, financial analysts and institutional investors common to both the suppliers and customers could undermine the informational advantages of other informed investors such as short sellers.

Given that short sellers are more likely to target firms with a poor information environment (Richardson 2003; Desai et al. 2006), they are more likely to direct their attention to supplier–customer pairs with fewer analysts and institutional investors in common. Short sellers can find more opportunities to trade the supplier stocks when there is less information diffusion along the supply chain with fewer analysts and institutional investors in common. Furthermore, previous studies have concluded that transient rather than dedicated or quasi-indexing institutional investors promptly transfer firm information to the market via frequent trading (Bushee 1998; Yan and Zhang 2009). This leads to our second hypothesis:

H2 The negative association between the short-sale volume of the supplier stocks around their customers' QEA and their customers' unexpected earnings is mitigated for the supplier–customer pairs that have analysts or transient institutional investors in common.

Customer information could be more valuable for customer–supplier pairs with stronger economic ties. Suppliers who depend more on their customers are likely to be more bound by the relationship due to the higher switching cost and less bargaining power (Pfeffer and Salancik 1978; Casciaro and Piskorski 2005). As a result, they are more sensitive to their major customers' performance. Suppliers and customers in a long-term relationship are more likely to form relational embeddedness (Polidoro et al. 2011). Relational embeddedness is characterized by closeness and trust (Moran 2005; Dong et al. 2015), which encourage coordinative activities and increase supply chain integration. Therefore, the duration of the supplier–customer relationship affects the strength of economic links between the supplier and customer. We thus predict that the negative relation between the unexpected earnings of the customer and the short-sale volume of the supplier stocks is more pronounced when the supplier firm is more dependent on its major customer and has a longer relationship with the major customer. This leads to our third hypothesis:

H3 The negative association between the short-sale volume of the supplier stocks around their customers' QEA and their customers' unexpected earnings is more pronounced for supplier–customer pairs where the dependence of the supplier on the customer is higher or the relationship duration is longer.

3 Data and sample

3.1 Short-sales data

Our daily short sales data are taken from the New York Stock Exchange (NYSE) TAQ-RegSHO database, which provides the short sales transactions for all stocks listed on the NYSE during the pilot period of January 3, 2005 to July 6, 2007. As a result, our sample period is limited to this time frame. Following Massoud et al. (2011), we aggregate the transaction-level data to the daily level for each stock.

3.2 Supplier–customer data

We identify supplier–customer relationships from the COMPUSTAT segment files.[6] Our method of doing so is similar to that of Fee and Thomas (2004). For each customer, we determine whether they are a Center for Research in Security Prices (CRSP)/COMPUSTAT listed firm. First, we use an algorithm to match customer names to the name file to obtain the unique customer identifiers, which is a COMPUSTAT segment file, and select the one with the smallest difference. Then, we conduct a visual inspection and use industry information to verify whether the one selected is indeed the customer of the supplier. Finally, we match the customer identifiers to identifiers in the COMPUSTAT, CRSP, Thomson Reuters (13f) Institutional Holdings and Institutional Brokers' Estimate System (I/B/E/S) databases to obtain fundamental customer information and information on institutional shareholdings and financial analysts. We exclude suppliers in the financial industries (Standard Industrial Classification (SIC) codes between 6000 and 6999).

3.3 Other data

The financial data are obtained from the COMPUSTAT database and the daily stock market data are obtained from the CRSP database. Information on the institutional investors are taken from Thomson Reuters (13f) Institutional Holdings database and financial analyst data from the I/B/E/S database.

4 Research design

To determine whether short sellers trade on customer information (H1), we carry out an event study around the customer QEA. The regression model is specified as follows:

$$\begin{aligned} CAVSS_{[-10,10]} = {} & \alpha_0 + \alpha_1 CustomerSUE + \alpha_2 Size + \alpha_3 Leverage \\ & + \alpha_4 ROA + \alpha_5 BM + \alpha_6 SalesGrowth + \alpha_7 Idiosyncraticrisk_{[-30,-11]} \\ & + \alpha_8 Return_{[-30,-11]} + \alpha_9 Volume_{[-30,-11]} + \sum\nolimits_{j} \alpha_{2j} Quarter_j \\ & + \sum\nolimits_{k} \alpha_{3k} IND_k + \omega \end{aligned} \tag{1}$$

[6] The majority of previous research on U.S. supplier–customer relationships in accounting and finance use the same data source (for example, Fee and Thomas 2004; Fee et al. 2006; Cohen and Frazzini 2008; Banerjee, Dasgupta, and Kim 2008; Hui et al. 2012).

$CAVSS_{[-10,\ 10]}$[7] is the cumulative abnormal short-sale volume on supplier firms over the event window of [−10, 10] days around the customer QEA, deflated by common shares outstanding. The abnormal short-sale volume is the daily short-sale volume minus normal short-sale volume which is the average short-sale volume over the estimation window of [−30, −11] days.[8] *Customer SUE* is the standardized unexpected earnings of customers. We measure *SUE* as the actual earnings per share at quarter *t* minus expected earnings per share at quarter *t*, scaled by the stock price at the end of the fiscal quarter. We use the actual earnings per share in the same quarter of the previous year as a proxy for the expected earnings per share in quarter *t*. Following Massoud et al. (2011), we control for firm size (*Size*), firm leverage (*Leverage*), return on assets (*ROA*), book-to-market ratio (*BM*), sales growth, idiosyncratic risk ($Idiosyncratic\ risk_{[-30,\ -11]}$), stock returns during the estimation window ($Return_{[-30,\ -11]}$), average daily trading volume over common shares outstanding during the estimation window ($Volume_{[-30,\ -11]}$), industry fixed effects based on Fama–French 48 industries (*IND*), and year-quarter fixed effects (*Quarter*) of the supplier firms. Detailed variable definitions are presented in the Appendix. If H1 holds, α_1 would be significantly negative. Standard errors are clustered by supplier–customer pair.

5 Empirical results

5.1 Descriptive statistics

Table 1 presents the descriptive statistics for the main variables used in the empirical analysis. To mitigate the effect of outliers, we winsorize all continuous variables at the 1st and 99th percentiles. Our full sample used in the regression analyses contains 2643 supplier–customer-quarters. The mean $CAVSS_{[-10,\ 10]}$ is 0.156 percent of the common shares outstanding, while the mean $CAVSS_{[-10,\ -1]}$ ($CAVSS_{[0,\ 10]}$) is 0.079 (0.077) percent of the common shares outstanding. If we use the event window of [−5, 5] days relative to the customer QEA to capture the short selling activities, the mean $CAVSS_{[-5,\ 5]}$ is 0.097 percent of the common shares outstanding, and the mean $CAVSS_{[-5,\ -1]}$ ($CAVSS_{[0,\ 5]}$) is 0.031 (0.066) percent of the common shares outstanding. It appears that the short-sale volume is higher after the customer earnings announcement, compared to that before the announcement.

The mean (median) *Customer SUE* is −0.011 (0.002), which suggests that more than half of the customer QEAs have a positive earnings surprise. For supplier firms, the mean *Size* is 7.642 and mean *Leverage* is 25%. The mean *ROA* is 1.7%. The mean *BM* and *Sales growth* for suppliers are 0.444 and 13.9%, respectively. The average idiosyncratic risk of the supplier firms estimated over the estimation window of [−30, −11] days is 0.016, and the average stock return of the supplier firms over this window is 0.001 which approaches 0, thus suggesting that little information of supplier firms has been disclosed during the estimation window. The average trading volume over common shares outstanding of the supplier firms is 8.323 over the estimation window, and the average R&D expenditures over total assets of the supplier firm is 0.7%.

7 Alternatively, we examine the short selling activities in the event window of [−5, 5] and [−3, 3] days relative to the QEAs of customers and report results in Tables 3 and 4.

8 Alternatively, we use the average daily short-sale volume of each supplier firm in our sample excluding observations in the event window of [−10, 10] days relative to the QEAs of customers to measure normal short-sale volume, and find our main results are qualitatively unchanged.

Table 1 Descriptive statistics

Variable	Obs	MEAN	STD	MIN	Q1	MEDIAN	Q3	MAX
$CAVSS_{[-10, 10]}$	2643	0.156	1.512	−5.006	−0.438	0.065	0.695	5.708
$CAVSS_{[-10, -1]}$	2643	0.079	0.924	−2.754	−0.291	−0.002	0.366	3.723
$CAVSS_{[0, 10]}$	2643	0.077	1.013	−4.956	−0.354	0.000	0.432	6.197
$CAVSS_{[-5, 5]}$	2643	0.097	1.073	−11.813	−0.301	0.004	0.387	7.449
$CAVSS_{[-5, -1]}$	2643	0.031	0.608	−5.527	−0.185	−0.017	0.163	5.079
$CAVSS_{[0, 5]}$	2643	0.066	0.679	−6.286	−0.199	−0.007	0.230	5.128
Customer SUE	2643	−0.011	0.089	−0.561	−0.004	0.002	0.007	0.249
Size	2643	7.642	1.384	4.811	6.691	7.615	8.548	11.566
Leverage	2643	0.250	0.172	0.000	0.134	0.233	0.353	0.750
ROA	2643	0.017	0.021	−0.071	0.010	0.017	0.026	0.097
BM	2643	0.444	0.262	−0.125	0.252	0.413	0.591	1.308
Sales growth	2643	0.139	0.265	−0.496	0.012	0.095	0.215	1.566
$Idiosyncratic\ risk_{[-30, -11]}$	2643	0.016	0.008	0.005	0.010	0.014	0.019	0.045
$Return_{[-30, -11]}$	2643	0.001	0.004	−0.012	−0.002	0.001	0.003	0.012
$Volume_{[-30, -11]}$	2643	8.323	6.489	0.752	4.007	6.452	10.484	36.273
R&D/total assets	2643	0.007	0.012	0.000	0.000	0.000	0.011	0.057
Sales dependence	2277	0.159	0.100	0.002	0.100	0.130	0.190	0.780
Duration	2643	5.132	4.348	1.000	2.000	4.000	7.000	30.000
COMAN	2643	0.337	0.473	0.000	0.000	0.000	1.000	1.000
%COMTRA	2643	0.133	0.074	0.000	0.091	0.143	0.185	0.290
$CAR_{[-10, 10]}$	2325	0.006	0.087	−0.242	−0.044	0.005	0.058	0.254
$Customer\ CAR_{[-10, 10]}$	2325	−0.194	2.609	−9.140	−0.638	−0.008	0.396	10.457

Definitions of variables are provided in the Appendix

For the supplier–customer relationships, the average percentage of supplier sales to a major customer (*Sales dependence*) is 16% and the average duration is 5.132 years. In 33.7% of the relationship-years, there are common analysts (*COMAN*) who follow both the supplier and customer. On average, 13.3% of the institutional investors of suppliers are transient institutional investors that hold stocks of both the supplier and customer (*%COMTRA*). In the event window of [− 10, 10] days relative to the customer QEA, the cumulative market-adjusted stock return of the suppliers is 0.6%, and that of the customers is − 19.4%.

5.2 Main results

We first conduct a univariate analysis and then a multivariate analysis to test whether short sellers trade on customer information and rely on private or public customer information, respectively.

Table 2 Univariate analysis

Customer SUE	$CAVSS_{[-10,\ 10]}$ (1)	$CAVSS_{[-5,\ 5]}$ (2)
1	0.453	0.297
2	0.133	0.166
3	0.102	0.056
4	0.289	0.172
5	0.108	0.040
6	0.205	0.087
7	−0.052	−0.019
8	0.114	0.053
9	0.174	0.154
10	0.047	0.015
1–10 diff	0.406***	0.282***
t value	3.15	3.19

We divide the full sample into ten groups based on *Customer SUE* for each year-quarter and examine how the short selling activities change across the ten groups. This table shows the average abnormal short-sale volume across groups. $CAVSS_{[-10,\ 10]}$ ($CAVSS_{[-5,\ 5]}$) is the cumulative abnormal short-sale volume of the suppliers over the event windows of [−10, 10] ([−5, 5]) days around the QEA of customers deflated by common shares outstanding and multiplied by 100. *** indicates significance at 1% level.

5.2.1 Univariate analysis

Table 2 presents the results of the univariate analysis. We divide the full sample into ten groups based on the deciles of *Customer SUE* (1 for the lowest and 10 for the largest customer SUE) and examine how short selling activities vary across the groups. Column 1 shows that the cumulative abnormal short-sale volume of the supplier stocks over the event window of [−10, 10] days relative to the QEA of customers ($CAVSS_{[-10,\ 10]}$) generally decreases with *Customer SUE*. The difference in $CAVSS_{[-10,\ 10]}$ between the lowest and the highest *Customer SUE* groups is significantly positive, as shown in the last line of the table. The results are qualitatively unchanged when we measure the short-sale volume of the supplier stocks over the event window of [−5, 5] days ($CAVSS_{[-5,\ 5]}$), as shown in Column 2.

5.2.2 Multivariate analysis

Table 3 presents the results of the multivariate analysis. Column 1 provides the results from the regression that does not include the control variables, which shows that the coefficient on *Customer SUE* is −1.087, and significantly negative at the 1% level, suggesting that the short-sale volume of the supplier stocks in a [10,10] window around the major customer's QEA is negatively associated with the customer's unexpected earnings, consistent with H1. After controlling for other variables in the regression model (Column 2), we still find a significantly negative association between *Customer SUE* and $CAVSS_{[-10,\ 10]}$.. As for the economic significance, if *Customer SUE* decreases from the third quartile (0.007 in Table 1) to the first quartile (−0.004 in Table 1), $CAVSS_{[-10,\ 10]}$ increases by 0.01 (0.912*0.011),

Table 3 Short-sale volume and customer SUE

	(1) [− 10, 10]	(2) [− 10, 10]	(3) [− 5, 5]
Intercept	0.144***	2.100***	1.092***
	(3.40)	(4.91)	(4.28)
Customer SUE	− 1.087***	− 0.912**	− 0.590**
	(− 2.97)	(− 2.42)	(− 2.32)
Size		− 0.102***	− 0.053**
		(− 2.92)	(− 2.38)
Leverage		− 0.439*	− 0.368**
		(− 1.72)	(− 2.21)
ROA		− 0.573	− 0.378
		(− 0.29)	(− 0.28)
BM		− 0.346**	− 0.199*
		(− 2.03)	(− 1.84)
Sales Growth		0.012	− 0.028
		(0.09)	(− 0.35)
Idiosyncratic risk$_{[-30,-11]}$/*Idiosyncratic risk*$_{[-30,-6]}$		− 32.998***	− 15.026***
		(− 5.98)	(-4.52)
Return$_{[-30,-11]}$/*Return*$_{[-30,-6]}$		− 28.602***	− 18.770***
		(− 3.59)	(− 3.21)
Volume$_{[-30,-11]}$/*Volume*$_{[-30,-6]}$		− 0.041***	− 0.015**
		(− 3.49)	(− 2.04)
Industry fixed effects	NO	YES	YES
Quarter fixed effects	NO	YES	YES
Adjusted R^2	0.004	0.126	0.069
Obs	2643	2643	2643

The dependent variable is $CAVSS_{[-10,\ 10]}$ ($CAVSS_{[-5,\ 5]}$) in Columns 1 and 2 (Column 3). Variables are defined in the Appendix. *t* statistics are in parentheses. Standard errors are clustered by supplier_customer pair. ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively

which is 6% of the average value of $CAVSS_{[-10,\ 10]}$. In Column 3, we measure the short-sale volume of the supplier stocks over the event window of [− 5, 5] days ($CAVSS_{[-5,\ 5]}$), and focus on short selling activities immediately around the customer QEA. We obtain similar results. In sum, the results support that short sellers trade on customer information and their trading volume increases when the customer's unexpected earnings are more negative.

The results for the control variables are generally consistent with those of previous research. For instance, firm size is negatively associated with cumulative abnormal short-sale volume, consistent with the result of Karpoff and Lou (2010). Firms with higher idiosyncratic risk have higher arbitrage costs (Shleifer and Vishny 1997), which explains for the negative association between idiosyncratic risk and cumulative abnormal short-sale volume. $Return_{[-30,\ -11]}$ is negatively associated with the cumulative abnormal short-sale volume, which is consistent with the view that short sellers exploit the momentum effect in the stock market to make a profit (Geczy et al. 2002). Stock trading volume

Table 4 Robustness checks

	An alternative measure of short-sale volume (1)	Control for supplier–customer pair fixed effects (2)	Control for supplier *SUE* (3)	Alternative event window [−3, 3] (4)
Customer SUE	−1.010*	−0.749*	−0.893**	−0.388**
	(−1.88)	(−1.81)	(−2.41)	(−2.28)
Supplier SUE			1.392**	
			(2.45)	
Controls	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES
Pair fixed effects	NO	YES	NO	NO
Quarter fixed effects	YES	YES	YES	YES
Adjusted R^2	0.102	0.291	0.128	0.059
Obs	2643	2643	2631	2643

This table presents the robustness check results. In Column 1, we deflate the cumulative abnormal short-sale volume of the suppliers in the event window of [−10, 10] days relative to the QEA of customers by their average stock trading volume in the estimation window. In Column 2, we control for the supplier–customer relationship and quarter fixed effects. In Column 3, we control for the effect of *supplier SUE*. The dependent variable in Columns 2–3 is $CAVSS_{[-10,\ 10]}$. In Column 4, we alternatively use the event window of [−3, 3] days relative to the QEA of customers to measure cumulative short-sale volume. Other variables are defined in the Appendix. Control variables in Model 1 are included but not reported for brevity. *t* statistics are in parentheses. Standard errors are clustered by supplier–customer pair. ***, ** and ** indicate significance at the 1%, 5% and 10% levels, respectively

($Volume_{[-30,\ -11]}$) in the estimation window is negatively associated with cumulative abnormal short-sale volume, which is consistent with Diether et al. (2008).

5.3 Robustness checks

We conduct four robustness tests. First, we use an alternative measure of abnormal short selling. Following Massoud et al. (2011), we scale the *CAVSS* in the test window by the average stock trading volume in the estimation window of [−30, −11] days instead of the number of common shares outstanding. The results are shown in Column 1 of Table 4. *Customer SUE* is significantly and negatively associated with the short-sale volume calculated for event windows of [−10, 10], consistent with our main findings.

Second, we control for the pair fixed effects and report the results in Column 2 of Table 4. After controlling for the pair fixed effects, the coefficient on *Customer SUE* is still significant, suggesting that our findings are not driven by omitted time-invariant pair level variables.

Third, we control for the effect of the supplier's *SUE*. One may argue that the negative association between *Customer SUE* on *CAVSS* is due to the positive association between the *SUE* of the customer firms and that of the supplier firms. If this is the case, then our significant result of Table 3 would become insignificant after we control for *Supplier SUE*. Column 3 of Table 4 confirms that this is not the case because the coefficient on *Customer SUE* remains significant after controlling for *Supplier SUE*.

Fourth, we measure short-sale volume of the supplier stocks in the event window of [−3, 3] days relative to the customer QEA.[9] Column 4 of Table 4 shows that the coefficient on *Customer SUE* is significant in the event window of [−3, 3], consistent with our main results.

5.4 Cross-sectional tests

5.4.1 Information environment of supplier–customer relationships

In this section, we consider the information environment of the supplier–customer relationships to test H2. Short sellers have lower information advantage if there are other information intermediaries who disseminate customer information into the market. Therefore, short-sellers are more likely to trade on customer information when common analysts of a supplier–customer pair are not present. Furthermore, short sellers are likely to earn higher returns from short selling stocks when there is a lower percentage of transient institutional investors in common with the customer among all of the supplier's institutional investors.

Specifically, we use the presence of common analysts (*COMAN*) and the percentage of common transient institutional investors (*%COMTRA*) among all institutional investors of suppliers respectively to capture the information environment of the supplier–customer pairs. *COMAN* is equal to 1 if the supplier and customer have at least one analyst in common, and 0 otherwise. *%COMTRA* is the ratio of the number of transient institutional investors in common with the customer over the total number of the supplier's institutional investors.[10]

To test H2, we interact *COMAN* (*%COMTRA*) with *Customer SUE*. If H2 holds, the coefficient on *COMAN* (*%COMTRA*) **Customer SUE* will be significantly positive. Column 1 of Table 5 indicates that the coefficient on *Customer SUE*COMAN* is significantly positive ($p < 0.10$), thus suggesting that the presence of common analysts mitigates the negative association between *Customer SUE* and the short-sale volume of the supplier stocks.[11] In Column 2 of Table 5, the coefficient on *Customer SUE*%COMTRA* is significantly positive ($p < 0.10$), which suggests that a higher percentage of common transient institutional investors mitigates the negative association between *Customer SUE* and the short-sale volume of the supplier stocks.[12] The results indicate that the supplier–customer

[9] For tests where short-sale volumes of the supplier stocks are measured in the event window of [−3, 3], *Idiosyncratic risk*, *Retur*n and *Volume* are measured in the event window of [−30, −4].

[10] We use the permanent identifiers of institutional investors, which are provided by Bushee (1998) and can be retrieved from his website (http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html), to determine whether the institutional investor is the common investor for both the supplier and customer (holds the stocks of both the supplier and customer).

[11] The results in Column 1 of Table 5 are qualitatively unchanged when we control for an indicator, which is 1 if the number of analysts that make earnings forecasts of suppliers is above the full sample median of the fiscal year and 0 otherwise, and its interaction with *Customer SUE*.

[12] The results in Column 2 of Table 5 are qualitatively unchanged when we control for an indicator, which is 1 if the number of institutional investors of suppliers is above the full sample median of the year-quarter and 0 otherwise, and its interaction with *Customer SUE*.

Table 5 Effects of information environment of supply chains

	(1)	(2)
*Customer SUE*COMAN*	1.384*	
	(1.79)	
Customer SUE%COMTRA*		7.708*
		(1.69)
Customer SUE	−1.385**	−1.376**
	(−2.55)	(−2.57)
COMAN	0.210*	
	(1.83)	
%COMTRA		−0.614
		(−1.14)
Controls	YES	YES
Industry fixed effects	YES	YES
Quarter fixed effects	YES	YES
Adjusted R^2	0.130	0.128
Obs	2643	2643

The dependent variable is $CAVSS_{[-10, 10]}$. For supplier–customer relationships where the supplier and customer are covered by the same analyst, *COMAN* = 1, otherwise, *COMAN* = 0. *%COMTRA* is the ratio of the number of common transient institutional investors between the supplier and customer over the number of institutional investors of the supplier firm. We follow Bushee (1998) to classify institutional investors into transient and non-transient (dedicated and quasi-indexing) institutional investors. Other variables are defined in the Appendix. Control variables in Model 1 are included but not reported for brevity. *t* statistics are in parenthesis. Standard errors are clustered by supplier–customer pair. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively

pairs that have analysts or transient institutional investors in common have a moderating effect, supporting H2.

5.4.2 Economic ties between the supplier and customer

In this section, we examine H3, i.e., how the economic ties between the supplier and customer affect short selling on customer information. We measure the economic ties between the supplier and customer based on three factors: sales dependence, R&D expenditures, or duration of relationship. We test whether the negative association in our main results are more pronounced for supplier firms that are more economically linked with their customers.

First, we calculate the percentage of sales of the supplier firm to the customer (Banerjee et al. 2008; Pandit et al. 2011) to measure the dependence of the supplier firm on the customer. Supplier firms with a higher percentage of sales to a specific customer tend to be more dependent on that customer. In Column 1 of Table 6, we interact *Customer SUE* with the percentage of sales of the supplier firm to the customer in the previous year (*Sales dependence*) and find that the coefficient on *Customer SUE*Sales dependence* is significantly negative ($p < 0.05$).

Table 6 Effects of economic ties

	(1)	(2)	(3)
*Customer SUE*Sales dependence*	−6.726**		
	(−2.45)		
*Customer SUE*High R&D*		−1.464**	
		(−1.99)	
*Customer SUE*Long Duration*			−1.487**
			(−2.01)
Customer SUE	0.325	−0.387	0.186
	(0.54)	(−1.07)	(0.34)
SDEP	0.356		
	(0.67)		
High R&D		0.184*	
		(1.72)	
Long Duration			0.123
			(1.60)
Controls	YES	YES	YES
Industry fixed effects	YES	YES	YES
Quarter fixed effects	YES	YES	YES
Adjusted R^2	0.138	0.130	0.129
Obs	1828	2643	2643

The dependent variable is $CAVSS_{[-10, 10]}$. *Sales dependence* is the percentage of supplier sales to the customer in the prior fiscal year. *High R&D* is 1 if R&D expenditures over total assets of supplier in the quarter before the QEA of customer is above the sample median of each year-quarter, and 0 otherwise. *Long Duration* is 1 if the duration of the relationship is longer than the sample median of each year-quarter, and 0 otherwise. Duration of the relationship is the number of years that we can observe the supplier–customer relationship at the end of the current fiscal year. Our data of supplier–customer relationships begin in 1976. Other variables are defined in the Appendix. Control variables in Model 1 are included but not reported for brevity. *t* statistics are in parentheses. Standard errors are clustered by supplier–customer pair. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively

Second, we use the supplier firm's ratio of the R&D expenditures over total assets (Kolay et al. 2016; Intintoli et al. 2017) to measure the dependence of the supplier firm on its customer. Supplier firms with higher R&D expenditures over total assets are likely to be more dependent on their customers. In Column 2, we interact *Customer SUE* with a dummy (*High R&D*) which is equal to 1 if the R&D expenditures over total assets of the supplier firm in the quarter prior to the customer QEA are higher than the year-quarter median, and 0 otherwise. We treat missing R&D expenditures as 0. The coefficient on *Customer SUE*High R&D* is significantly negative ($p < 0.05$).

Third, a long-term customer–supplier relationship generates social embeddedness and thus increases the economic ties between the supplier and customer. In Column 3 of Table 6, we interact *Customer SUE* with an indicator of the duration of the relationship (*Long Duration*), which equals 1 if the number of years that we can observe the supplier–customer relationship at the end of the current fiscal year is longer than the

Table 7 The effect of overpricing of suppliers' stocks

	(1)	(2)
Customer SUE	−1.181***	−1.521***
	(−2.62)	(−2.90)
*Customer SUE*Overpricing*		0.701
		(0.84)
*Customer SUE*Underpricing*		0.508
		(0.46)
Overpricing	0.141	0.152
	(1.35)	(1.43)
Underpricing	−0.266***	−0.260***
	(−2.77)	(−2.76)
Other controls	YES	YES
Industry fixed effects	YES	YES
Quarter fixed effects	YES	YES
Adj. R^2	0.147	0.146
Obs	2136	2136

The dependent variable is $CAVSS_{[-10, 10]}$. *Overpricing* (*Underpricing*) is 1 if the level of stock overpricing, measured by Stambaugh et al. (2015) is in the upper (lower) tercile of its distribution for each month, and 0 otherwise. Other variables are defined in the Appendix of the paper. Control variables in Model 1 are included but not reported for brevity. *t* statistics are in parentheses. Standard errors are clustered by supplier–customer pair. ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively

year-quarter median, and 0 otherwise.[13] The coefficient on *Customer SUE*Long Duration* is significantly negative ($p < 0.05$). In sum, these findings indicate that the relation between *Customer SUE* and the short-sale volume of the supplier stocks is more pronounced for supplier–customer pairs who have closer economic ties, supporting H3.

5.4.3 Overpricing of suppliers' stocks

In this subsection, we examine whether the main anomalies other than the supplier–customer anomaly which cause the overpricing of suppliers' stocks explain our results and how these anomalies affect our results. We rely on the measure of Stambaugh et al. (2015) to capture the level of overpricing of suppliers' stocks[14] in the month of customer QEAs. *Overpricing* (*Underpricing*) is 1 if the level of stock overpricing, measured by Stambaugh

[13] Our data of supplier–customer relationships begin in 1976.

[14] Stambaugh et al. (2015) construct the measure of a firm's stock overpricing based on the following eleven anomalies identified in the literature: financial distress probability, O-score bankruptcy probability, net stock issues, composite equity issues, total accruals, net operating assets, momentum, gross profitability, asset growth, return on assts and investment-to-assets. The measure is the average of the ranking percentile for each of the eleven anomalies. Stocks with highest values of the measure are the most overpriced and those with the lowest values of the measure are the most underpriced. The data is available via Professor Stambaugh's website: https://finance.wharton.upenn.edu/~stambaug/.

et al. (2015) is in the upper (lower) tercile of its distribution for each month, and 0 otherwise. Table 7 provides the results.

Column 1 of Table 7 shows that the coefficient on *Overpricing* is positive but insignificant and the coefficient on *Underpricing* is significantly negative ($p < 0.01$), consistent with the literature that short sellers exploit the overpricing of stocks (Safieddine and Wilhelm 1996; Dechow et al. 2001; Kot 2007). More importantly, the coefficient on *Customer SUE* is still significantly negative ($p < 0.01$). In Column 2 of Table 7, we interact *Customer SUE* with *Overpricing/Underpricing* and find that the coefficients on the interaction terms are not significant. These results suggest that the supplier–customer anomaly is distinct from and probably independent of the anomalies captured by our measure of stock overpricing, and short sellers exploit both.[15]

5.5 Further tests

In this section, we conduct four additional tests: whether short sellers trade on public or private customer information, how short-sale constraints affect short selling on customer information, whether customer SUE can predict the supplier's future performance, and whether short sellers trade on firm-specific or macro-based information implied by the customer SUE.

5.5.1 Do short sellers trade on public or private customer information?

Short sellers' trading of supplier stocks around major customer earnings announcement could be driven by their superior ability to interpret publicly available information (e.g., Asquith and Meulbroek 1995; Dechow et al. 2001; Engelberg et al. 2012), their access to private information (e.g., Christophe et al. 2004, 2010; Desai et al. 2006; Massoud et al. 2011; Khan and Lu 2013), or both (Boehmer et al. 2020). In this subsection, we investigate the underlying mechanism that drives the short selling of supplier stocks around customer earnings announcement.

5.5.1.1 Short-sale volume before or after the customer QEA and customer SUE Following Massoud et al. (2011), we divide the event window into two parts based on whether the trading days are before or after the announcement of the customer QEA. If short sellers rely on the private information of customers, the coefficient on *Customer SUE* (α_1) would be significantly negative for the event window before the customer QEA. If short sellers gain information advantage due to their sophisticated skills in processing public information, α_1 would be insignificant for the event window before the customer QEA, but significantly negative for the event window after the customer QEA. If both the sophisticated information processing skills and the access to private information contribute to the short sales of supplier stocks, α_1 would be significant for both before and after event windows.

We calculate the *CAVSS* across various event windows of [− 10, − 1], [0, 10], [− 5, − 1], [0, 5], [− 3, − 1] and [0, 3] days relative to the announcement of the customer QEA in Columns 1–6 of Table 8. In Column 1 where the dependent variable is *CAVSS* across

15 The results of *Customer SUE**Overpricing* (*Customer SUE**Underpricing*) do not change if we measure short-sale volume around customer QEAs in the window of [-10, -1] or [0,10] regarding the trading activities on public/private information.

Table 8 Trading on public or private information of customers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	[− 10, − 1]	[0, 10]	[− 5, − 1]	[0, 5]	[− 3, − 1]	[0, 3]	[− 10, 10]	[− 10, − 2]	[− 1, 10]	[− 5, − 2]	[− 1, 5]	[− 3, − 2]	[− 1, 3]
Customer SUE	− 0.251	− 0.661**	− 0.176	− 0.414**	− 0.084	− 0.304**	0.255	− 0.242	− 0.756**	− 0.154	− 0.423**	− 0.064	− 0.342**
	(− 1.05)	(− 2.55)	(− 1.31)	(− 2.41)	(− 1.04)	(− 2.35)	(0.21)	(− 1.11)	(− 2.52)	(− 1.31)	(− 2.20)	(− 0.98)	(− 2.28)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.067	0.106	0.036	0.064	0.029	0.053	0.136	0.061	0.112	0.031	0.072	0.022	0.059
Obs	2643	2643	2643	2643	2643	2643	422	2643	2643	2643	2643	2643	2643

The dependent variables are *CAVSS* in the event windows indicated by the title of each column. Except Column 7 where we restrict our sample to the *first year* of each supplier–customer relationship, all columns report the results of our final full sample. Variables are defined in the Appendix. *t* statistics are in parenthesis. Standard errors are clustered by supplier–customer pair. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively the pre-announcement event window of [− 10, − 1] days, the coefficient on *Customer SUE* is insignificant. In Column 2 where the dependent variable is *CAVSS* across the post-announcement event window of [0, 10] days, the coefficient on *Customer SUE* is − 0.661 and statistically significant ($p<0.05$). The contrasting results in Columns 1 and 2 suggest that short sellers tend to trade on public rather than private customer information.[16] In Columns 3–4 (Columns 5–6), we employ alternative event windows of [− 5, − 1] and [0, 5] days ([− 3, − 1] and [0, 3] days), and obtain similar results. The coefficient on *Customer SUE* is significantly negative for the *CAVSS* across the post-announcement event window of [0, 5] ([0, 3]) days, but insignificant across the pre-announcement event window of [− 5, − 1] ([− 3, − 1]) days.

Following Alldredge and Cicero (2015), we examine in Column 7 whether the negative association between *Customer SUE* and $CAVSS_{[-10,\ 10]}$ holds in the *first year* of the supplier–customer relationship. The supplier–customer relationship is publicly available only after the supplier issues its annual report, which means that during the first year of the relationship, outsiders without private information would not know about the establishment of the relationship. If short sellers trade on private customer information, we expect to find a significant association in this restricted subsample. However, the coefficient on *Customer SUE* is insignificant in Column 7 of Table 8, which further suggests that short sellers trade on the public customer information.

Lastly, we consider information leakage in the day before customer earnings announcements. Columns 8–13 of Table 7 show that the coefficient on *Customer SUE* is significantly negative in event windows of [− 1, 10], [− 1, 5] and [− 1, 3], but insignificant in event windows of [− 10, − 2], [− 5, − 2] and [− 3, − 2], consistent with our prior results.

5.5.1.2 Daily short-sale volume and customer SUE Our results in Table 8 are based on the aggregated cumulative abnormal short-sale volume over multiple days, which represents the *net* abnormal volume of multiple days. Next, we further examine the time-varying effects of customer SUE on the *daily* abnormal short-sale volume of the supplier stocks around the customer QEA. Specifically, we regress the daily abnormal short-sale volume of the supplier stocks, deflated by common shares outstanding and multiplied by 100, on *Customer SUE*. Table 9 summarizes the results. *AVSS* with a subscript i refers to the abnormal short-sale volume of the supplier stocks at day i relative to the customer QEA.

Panel A provides the results of daily short-sale volume for the pre-announcement period from -10 to -1, respectively. None of the coefficients on *Customer SUE* is significant before the customer QEA. Panel B provides the results of daily short-sale volume on or after the customer QEA. The coefficient on *Customer SUE* is significantly negative at day 0, suggesting that short sellers trade on customer information timely once earnings are released. The coefficients on *Customer SUE* are also significantly negative in some of post-announcement periods, i.e., day 3, day 4, day 6, day 7, and day 8, suggesting a continuous trading of short sellers following the disclosure of customer information. Overall, the results based on daily short-sale volume suggest that short sellers react to the customer information immediately after the information is disclosed, also confirming that short sellers mainly trade on the public customer information.

[16] The results are qualitatively unchanged when we control for the level of stock overpricing/underpricing of suppliers.

Table 9 Daily short-sale volume and customer SUE

	$AVSS_{-10}$	$AVSS_{-9}$	$AVSS_{-8}$	$AVSS_{-7}$	$AVSS_{-6}$	$AVSS_{-5}$	$AVSS_{-4}$	$AVSS_{-3}$	$AVSS_{-2}$	$AVSS_{-1}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
Panel A: Daily short-sale volume at [− 10, − 1]											
Customer SUE	0.001	−0.000	−0.000	−0.000	0.000	−0.000	−0.001	−0.000	−0.000	−0.000	
	(1.57)	(−0.53)	(−0.92)	(−0.56)	(0.27)	(−1.05)	(−1.47)	(−1.10)	(−0.70)	(−0.79)	
Adj. R^2	0.045	0.026	0.032	0.047	0.032	0.021	0.024	0.047	0.036	0.061	
Obs	2643	2643	2643	2643	2643	2643	2643	2643	2643	2643	
	$AVSS_{0}$	$AVSS_{1}$	$AVSS_{2}$	$AVSS_{3}$	$AVSS_{4}$	$AVSS_{5}$	$AVSS_{6}$	$AVSS_{7}$	$AVSS_{8}$	$AVSS_{9}$	$AVSS_{10}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel B: Daily short− sale volume at [0, 10]											
Customer SUE	−0.001**	−0.001	−0.048	−0.001**	−0.000*	−0.000	−0.001*	−0.001***	−0.001***	−0.000	−0.000
	(−2.31)	(−1.56)	(−1.23)	(−2.27)	(−1.68)	(−0.19)	(−1.84)	(−2.64)	(−2.96)	(−0.93)	(−0.07)
Adj. R^2	0.063	0.041	0.054	0.052	0.048	0.027	0.038	0.049	0.053	0.039	0.044
Obs	2643	2643	2643	2643	2643	2643	2643	2643	2643	2643	2643

This table shows the effect of customer SUE on daily abnormal short-sale volume over the event window of [− 10, 10] days relative to the QEA of customers. The dependent variable is daily abnormal short-sale volume of the supplier firm deflated by common shares outstanding and multiplied by 100 (*AVSS*). Control variables in Model 1 are included but not reported for brevity. *t* statistics are in parentheses. Standard errors are clustered by supplier–customer pair. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively

Table 10 Information environment of supply chains and daily short selling on private information of customers

	$AVSS_{-10}$	$AVSS_{-9}$	$AVSS_{-8}$	$AVSS_{-7}$	$AVSS_{-6}$	$AVSS_{-5}$	$AVSS_{-4}$	$AVSS_{-3}$	$AVSS_{-2}$	$AVSS_{-1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Common analysts										
Customer SUE	0.055	0.015	−0.023	−0.035	−0.003	−0.106***	−0.132*	−0.067	−0.062	−0.052
	(1.09)	(0.28)	(−0.45)	(−0.82)	(−0.08)	(−2.67)	(−1.95)	(−1.47)	(−1.31)	(−1.22)
*Customer SUE*COMAN*	0.002	−0.115	−0.035	0.049	0.022	0.180***	0.191**	0.089	0.114**	0.080
	(0.04)	(−1.45)	(−0.47)	(0.97)	(0.45)	(3.00)	(2.04)	(1.52)	(2.17)	(1.56)
COMAN	−0.003	−0.014	−0.001	0.000	−0.004	−0.010	0.003	0.010	0.021**	0.010
	(−0.31)	(−1.62)	(−0.12)	(0.03)	(−0.48)	(−1.03)	(0.37)	(1.20)	(2.01)	(1.14)
Adj. R^2	0.044	0.027	0.031	0.046	0.032	0.025	0.027	0.047	0.039	0.061
Obs	2643	2643	2643	2643	2643	2643	2643	2643	2643	2643
Panel B: Common institutional investors										
Customer SUE	0.034	0.003	−0.052	−0.042	−0.005	−0.093**	−0.118*	−0.066	−0.047	−0.042
	(0.68)	(0.05)	(−1.02)	(−0.99)	(−0.15)	(−2.30)	(−1.76)	(−1.46)	(−1.00)	(−0.99)
Customer SUE%COMTRA*	0.325	−0.437	0.273	0.440	0.160	0.946**	0.997*	0.491	0.378	0.306
	(0.95)	(−0.79)	(0.73)	(1.47)	(0.57)	(2.54)	(1.71)	(1.47)	(1.21)	(0.99)
%COMTRA	−0.118**	−0.068	−0.009	−0.063	−0.085*	−0.158***	−0.109*	−0.087*	−0.067	−0.056
	(−2.21)	(−1.13)	(−0.21)	(−1.25)	(−1.68)	(−2.70)	(−1.84)	(−1.96)	(−1.31)	(−1.21)
Adj. R^2	0.047	0.025	0.030	0.046	0.036	0.030	0.032	0.052	0.037	0.063
Obs	2626	2626	2626	2626	2626	2626	2626	2626	2626	2626

This table shows how the information environment of supply chains affects the effect of customer SUE on daily abnormal short-sale volume over the event window of [−10, −1] days relative to the QEA of customers. The dependent variable is daily abnormal short-sale volume of the supplier firm deflated by common shares outstanding and multiplied by 100 (*AVSS*). Control variables in Model 1 are included but not reported for brevity. *t* statistics are in parentheses. Standard errors are clustered by supplier–customer pair. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively

5.5.2 Information environment of supply chains and daily short selling on customer private information

Prior literature (e.g., Diamond 1985; Brown et al. 2004) suggests that private information acquisition is positively associated with information asymmetry. Therefore, we further examine whether the information environment of supply chains affects short sellers' incentives to exploit private information of customers. In Panel A of Table 10, we use the presence of common analysts between the supplier and customer (*COMAN*) to proxy for the information transparency of supply chains. The coefficient on *Customer SUE* is significantly negative for daily abnormal short-sale volume on day -5 and -4 relative to the earnings announcements of customers. It suggests that short sellers trade on private information of customers for relationships without common analysts. We also use the percentage of common transient institutional investors among all institutional investors of suppliers (*%COMTRA*) to measure the information transparency of supply chains. The results reported in Panel B of Table 10 remain consistent. These results provide some evidence that short sellers trade on the private information of customers in the circumstances where investors of suppliers are inattentive to customer information. The coefficient on the interaction term between *Customer SUE* and *COMAN* (*%COMTRA*) is significantly positive on day -5 and -4 respectively, which are consistent with H2.

5.6 Short-sale constraint

Short-sale constraint limits the short selling behavior. Prior literature shows that stock lenders are mainly institutional investors (e.g., Asquith et al. 2005; Nagel 2005). So, firms with lower institutional ownership have higher short-sale constraint. In addition, the Regulation SHO provides us an exogenous measure of short-sale constraint. Under this regulation, approximately 1000 firms in the Russell 3000 index are randomly selected to be exempted from the uptick test.[17] Firms that are exempted from the uptick test have lower short-sale constraint. We thus use either institutional ownership (*INST*) of suppliers or an indicator of suppliers exempted from the uptick test (*Exempted*) as a proxy for short-sale constraint of suppliers and interact each of the proxy with *Customer SUE* in Model 1. Panel A of Table 11 presents the results. Both coefficients on the interaction terms are significantly negative, suggesting that our main results are more pronounced for supplier–customer pairs where the short-sale constraint of the supplier is lower.

5.7 Customer SUE and future operating performance of suppliers

In our empirical analyses, we assume that it is profitable for short sellers to trade on more negative customer SUE. This assumption lies in the predictability of customer SUE to the supplier future operating performance. We thus conduct an additional test on the relation between customer SUE and the supplier future operating performance. We measure the supplier future operating performance using operating income before depreciation, divided by total assets in the fiscal quarter that ends after the customer QEA.

[17] Every third stock ranked by average daily trading volume during the year before the pilot program was announced in the index are selected (Securities and Exchange Commission 2007).

Table 11 Further tests

	(1)	(2)
Panel A: Short-sale constraint		
*Customer SUE*INST*	− 5.693***	
	(− 4.91)	
*Customer SUE*Exempted*		− 2.416***
		(− 3.02)
Customer SUE	3.241***	1.416*
	(4.78)	(1.94)
INST	0.671***	
	(3.19)	
Exempted		0.079
		(0.60)
Controls	YES	YES
Industry fixed effects	YES	YES
Quarter fixed effects	YES	YES
Adjusted R^2	0.125	0.127
Obs	2355	2643
Panel B: Customer SUE and future performance of suppliers		
Intercept	0.037***	0.019***
	(39.26)	(6.71)
Customer SUE	0.012***	0.008*
	(2.78)	(1.76)
Industry fixed effects	NO	YES
Quarter fixed effects	NO	YES
Adjusted R^2	0.002	0.197
Obs	2562	2562
Panel C: Short-sale volume and the components of customer SUE		
Macro Customer SUE	− 84.992	− 71.244
	(− 1.50)	(− 1.27)
Firm-specific Customer SUE	− 1.039***	− 0.871***
	(− 3.18)	(− 2.62)
Controls	NO	YES
Industry fixed effects	NO	YES
Quarter fixed effects	NO	YES
Adjusted R^2	0.005	0.127
Obs	2643	2643

Panel A presents the effect of short-sale constraint on short selling on customer information. Panel B presents the effect of customer SUE and future performance of suppliers. The dependent variable is operating income before depreciation, divided by total assets in the fiscal quarter ending after the QEA of customer. Panel C presents the effect of components of customer SUE and short-sale volume of stocks of suppliers. We follow Israeli et al. (2017) to decompose unexpected earnings of customer into those that are macro-based and firm specific. Control variables in Model 1 are included but not reported for brevity. *t* statistics are in parentheses. Standard errors are clustered by supplier–customer pair. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively

Panel B of Table 11 presents the results. For the univariate test results in Column 1, the coefficient on *Customer SUE* is significantly positive ($p < 0.01$). In Column 2 which includes the industry and year-quarter fixed effects, the result remains significantly positive. The evidence indicates that customer SUE indeed predicts the supplier future performance, which makes short selling on customer SUE profitable.

5.8 Short-sale volume and different components of customer SUE

Both macro-based and firm-specific factors affect a firm's SUE (Israeli et al. 2017). Compared with firm-specific component of SUE, macro-based component of SUE is more attentive to investors because investors can get the macro-based information from other firms in the same year (for information specific to a year) or industry-year (for information specific to an industry-year). As a result, we predict that the information advantage of short sellers is mainly derived from the firm-specific information of customers and that short sellers mainly trade on the firm-specific information implied by customer SUE. Following Israeli et al. (2017), we decompose the customer's unexpected earnings (SUE) into the macro-based component and firm-specific component. The macro-based (firm-specific) unexpected earnings are the predicted (residual) value of the SUE regressed on the value-weighted SUE of all the Compustat firms in the same fiscal quarter and the value-weighted SUE of all Compustat firms in the same Fama–French 48 industry and fiscal quarter. We then replace SUE by these two components separately in Model 1.

Panel C of Table 11 presents the results. The coefficient on *Firm-specific Customer SUE* is significantly positive in both columns ($p < 0.01$), regardless of whether the control variables are included. In contrast, the coefficient on *Macro Customer SUE* is not significant in either column. The results suggest that short sellers mainly trade on firm-specific information of major customers, consistent with our prediction.

6 Economic consequence of short selling on customer information

Our previous results indicate that short sellers have an information advantage on customer information and their information advantage is largely derived from their sophisticated interpretation of public information, although we find some evidence of their trading on private information. An important economic consequence of short selling on customer information is that short selling improves the conveyance of customer information on the supplier stock prices. Given the role of short sellers in disseminating negative information, we expect the improvement to be more pronounced for negative customer information. To test the validity of this claim, we begin with a univariate analysis to determine whether the correlation between the stock returns of the supplier and customer around the customer QEA increases with short-sale volume and whether the increase is more imminent for relationships with a negative *Customer SUE*.

In Panel A of Table 12, the full sample is divided into 5 quintiles based on $CAVSS_{[-10,\,10]}$. It can be observed that the correlation coefficients between the cumulative abnormal stock returns (CAR) of the supplier and customer in the event window increase with the $CAVSS_{[-10,\,10]}$ quintile from 0.014 to 0.119, although the increase is not monotonic. The increase in the correlation coefficients with $CAVSS_{[-10,\,10]}$ is more evident for the negative *Customer SUE*.

Table 12 Economic consequence of short selling on customer information

	Full sample		*Customer SUE < 0*		*Customer SUE ≥ 0*	
Quintile	N	Corr ($CAR_{[-10, 10]}$, $Customer\ CAR_{[-10, 10]}$)	N	Corr ($CAR_{[-10, 10]}$, $Customer\ CAR_{[-10, 10]}$)	N	Corr ($CAR_{[-10, 10]}$, $Customer\ CAR_{[-10, 10]}$)
Panel A: Univariate analysis						
1	465	0.014	128	−0.094	337	0.059
2	465	0.118	142	0.298	323	0.055
3	465	0.151	124	0.174	341	0.141
4	465	0.097	125	0.073	340	0.106
5	465	0.119	167	0.089	298	0.132
Q5-Q1		0.105		0.183		0.072

	Full sample (1)	High short-sale volume		Low short-sale volume	
		Customer SUE ≥ 0 (2)	*Customer SUE < 0* (3)	*Customer SUE ≥ 0* (4)	*Customer SUE < 0* (5)
Panel B: Multivariate analysis					
Intercept	−0.014	0.042	−0.180**	0.038	−0.187***
	(−0.48)	(0.71)	(−2.20)	(1.06)	(−3.20)
Customer CAR	0.002***	0.002	0.013**	0.001	0.007
	(3.31)	(1.44)	(2.08)	(1.34)	(1.22)
Size	0.001	0.001	0.003	−0.000	0.008**
	(0.63)	(0.36)	(0.58)	(−0.14)	(2.26)
Leverage	0.015	−0.012	0.019	0.009	0.043
	(1.11)	(−0.50)	(0.40)	(0.51)	(1.24)
ROA	0.303***	0.223	0.577	0.193	0.598**
	(2.73)	(1.21)	(1.53)	(1.28)	(2.11)
BM	0.036***	0.061***	0.026	0.018	0.065***
	(4.21)	(3.22)	(1.11)	(1.50)	(3.07)
Sales Growth	0.008	−0.001	0.006	0.010	0.003
	(1.09)	(−0.07)	(0.22)	(0.88)	(0.22)
Idiosyncratic $risk_{[-30, -11]}$	1.033***	2.107**	3.558***	0.129	1.920**
	(2.83)	(2.37)	(2.83)	(0.35)	(2.44)
$Return_{[-30, -11]}$	−1.499***	0.159	−1.538	−1.875***	−2.274**
	(−3.02)	(0.15)	(−0.79)	(−3.19)	(−2.01)
$Volume_{[-30, -11]}$	−0.000	−0.001	−0.003*	0.001**	−0.000
	(−0.83)	(−1.01)	(−1.85)	(2.13)	(−0.24)
Industry fixed effects	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES
Adjusted R^2	0.046	0.054	0.080	0.069	0.119
Obs	2325	807	356	832	330

Table 12 (continued)

	Full sample (1)	High short-sale volume		Low short-sale volume	
		Customer SUE ≥ *0* (2)	*Customer SUE* < *0* (3)	*Customer SUE* ≥ *0* (4)	*Customer SUE* < *0* (5)
Difference in the coef. on *Customer CAR* between groups		0.011* (1.82)			

This table presents the economic consequence of shortselling on customer information. Panel A shows the univariate analysis results. The full sample is divided into 5 quintiles based on $CAVSS_{[-10,\ 10]}$. Panel B presents the multivariate analysis results. The dependent variable is $CAR_{[-10,\ 10]}$, cumulative abnormal stock return of suppliers in the event window of [− 10, 10] days relative to the QEA of customer. The abnormal stock return is the market-adjusted stock return. High (Low) short-sale volume is the subsample group that is above (below) the sample median of $CAVSS_{[-10,\ 10]}$. *t* statistics are in parentheses. Standard errors are clustered by supplier–customer pair. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

We further conduct a multivariate analysis to test whether short selling increases the contemporary association of the customer and supplier stock returns and report the results in Panel B of Table 12. The dependent variable is the supplier's cumulative abnormal (i.e., market-adjusted) stock return in the event window of [-10, 10] days relative to the customer QEA ($CAR_{[-10,\ 10]}$). The variable of interest is the customer's cumulative abnormal stock return in the event window of [-10, 10] days relative to the customer QEA (*Customer CAR*). To show the effect of short selling on the association of the customer and supplier stock returns, we divide the full sample into four subgroups based on whether the short-sale volume ($CAVSS_{[-10,\ 10]}$) is above (i.e., group with high short-sale volume) or below (i.e., group with low short-sale volume) the sample median, and whether the customer information (*Customer SUE*) is nonnegative (i.e., *Customer SUE* ≥ 0 group) or negative (i.e., *Customer SUE* < 0 group). We include all control variables shown in Model 1.

In Column 1 for the full sample, *Customer CAR* is significantly positively associated with supplier *CAR* ($p < 0.01$). However, this positive association exists only in the subgroup with a high short-sale volume and negative *Customer SUE*, as shown in Column 3. The results in Table 12 support our prediction that short selling increases the conveyance of negative customer information along supply chains and improves stock price efficiency for the suppliers.

7 Conclusions

Using the daily short-selling data derived from the TAQ-RegSHO database, this study examines whether short sellers trade the supplier stocks based on customer information. Using *Customer SUE* as a proxy for customer information, we find that short sellers use customer information in their trading decisions. Our cross-sectional analyses show that the negative association between the cumulative abnormal short-sale volume of supplier stocks and customer earnings performance is mitigated by the presence of supply chain analysts or a higher percentage of common transient institutional investors who hold the stocks of both suppliers and customers. We also find that the negative association is intensified by stronger economic ties between the suppliers and customers. These results indicate that short sellers target firms with opaque information environments and supplier–customer relationships with stronger economic ties. Our additional analyses show that though short sellers largely trade on public customer information, they also trade on private customer information in the circumstance where investors of suppliers are inattentive to customer information (i.e., relationships without common analysts or with fewer common transient institutional investors). In addition, we find that short sellers trade on firm-specific earning information of customers rather than macro-based information and that our main results are more pronounced when the short-sale constraint of the supplier is lower. These robustness tests strengthen the validity of our results. Finally, we provide evidence that short selling on customer information significantly improves the conveyance of customer information along supply chains.

Our study identifies an important force that has been largely neglected in the literature, i.e., short sellers, who can enhance information flow along supply chains and mitigate the customer–supplier anomaly. This study adds to the growing body of literature on information transfer along supply chains. It also adds to the literature on the behaviors of short sellers by showing that short sellers exploit the underreaction of customer information in the stock market. Managers or investors of suppliers may rely on the abnormal short-sale volume around customer events to detect the supply chain risk. We use customer SUE to measure the customer information and do not look at the information of customers unrelated to SUE. Future research may examine whether short sellers trade on information of customers other than SUE and compare the importance of different types of customer information for short sellers. Due to data availability, we restrict our sample period from January 3, 2005 to July 6, 2007. Future research may extend the sample period by using other data sources and check whether the results of this study are sensitive to sample periods.

Appendix

See Table 13.

Table 13 Variable definitions

Variable	Definition
AVSS	Daily abnormal short-sale volume of stocks of suppliers deflated by the number of common shares outstanding and multiplied by 100. Abnormal short-sale volume is the difference between short-sale volume and normal short-sale volume which is the average short-sale volume over the event window of [− 30, − 11] days for a test window of [− 10, 10] days or [− 30, − 6] days for a test window of [− 5, 5] days around QEA of customers
$CAVSS_{[-10,\,10]}/CAVSS_{[-5,\,5]}/CAVSS_{[-3,\,3]}$	Cumulative *AVSS* over the event window of [− 10, 10]/[− 5, 5]/[− 3, 3] days around QEA of customers
$CAVSS_{[-10,\,-1]}/CAVSS_{[-5,\,-1]}/CAVSS_{[-3,\,-1]}$	Cumulative *AVSS* over the event window of [− 10, − 1]/[− 5, − 1]/[− 3, − 1] days around QEA of customers
$CAVSS_{[0,\,10]}/CAVSS_{[0,\,5]}/CAVSS_{[0,\,3]}$	Cumulative *AVSS* over the event window of [0, 10]/[0, 5]/[0, 3] days around QEA of customers
Customer SUE	Standardized unexpected earnings (SUE) of customer. SUE is measured as the change in basic earnings per share before extraordinary items from the same fiscal quarter in the prior year to the current fiscal quarter, deflated by the stock price at the end of the fiscal quarter
Size	Natural logarithm of total assets of the supplier firm
Leverage	Total debt/Total assets of the supplier firm
ROA	EBIT/Total assets of the supplier firm
BM	Book value of equity/(Common shares outstanding*Price at the end of this quarter) of the supplier firm
Sales Growth	Growth rate of sales of the supplier firm, calculated as the change in net sales from the same fiscal quarter in the prior year to the current fiscal quarter, divided by net sales of the same fiscal quarter in the prior year
$Idiosyncratic\ risk_{[-30,\,-11]}/Idiosyncratic\ risk_{[-30,\,-6]}$	The supplier's standard deviation of residuals of the market model, estimated by using daily data in the event window of [− 30, − 11]/[− 30, − 6] days relative to the QEA of customers
$Return_{[-30,\,-11]}/Return_{[-30,\,-6]}$	The average stock returns of the supplier in the event window of [− 30, − 11]/[− 30, − 6] days relative to the QEA of customers
$Volume_{[-30,\,-11]}/Volume_{[-30,\,-6]}$	The average trading volume over the number of common shares outstanding of the supplier in the event window of [− 30, − 11]/[− 30, − 6] days relative to the QEA of customers
Supplier SUE	Standardized unexpected earnings (SUE) of supplier
COMAN	Dummy variable, equal to 1 if the supplier and customer have at least one analyst in common, and 0 otherwise
%COMTRA	The ratio of the number of transient institutional investors the supplier and customer have in common over the number of institutional investors of the supplier

Table 13 (continued)

Variable	Definition
Sales Dependence	Percentage of supplier sales to the customer
High R&D	Dummy variable, equal to 1 if the R&D expenditures over total assets of the supplier firm in the fiscal quarter prior to the QEA of customers (*R&D/total assets*) is above the year-quarter median, and 0 otherwise. Missing R&D expenditures is treated as 0
Long Duration	Dummy variable, equal to 1 if the duration of the relationship is above the year-quarter median, and 0 otherwise. Duration of the relationship is number of years that we can observe the supplier–customer relationship at the end of the current fiscal year. Our data of supplier–customer relationships begin in 1976
Overpricing	1 if the level of stock overpricing, measured by Stambaugh et al. (2015) is in the upper tercile of its distribution for each month, and 0 otherwise
Underpricing	1 if the level of stock overpricing, measured by Stambaugh et al. (2015) is in the lower tercile of its distribution for each month, and 0 otherwise
INST	Total institutional ownership of suppliers at the end of the quarter
Exempted	1 if the supplier has short sales exempted from uptick test, and 0 otherwise
Macro Customer SUE	The predicted value of SUE regressed on value-weighted SUE in the market and value-weighted SUE in the industry of the customer. Industry classification is based on Fama–French 48 industries
Firm-specific Customer SUE	The residual value of SUE regressed on value-weighted SUE in the market and value-weighted SUE in the industry of the customer. Industry classification is based on Fama–French 48 industries
$CAR_{[-10, 10]}$	Cumulative market-adjusted stock return of the supplier firm in the event window of [− 10, 10] days relative to the QEA of customers
Customer $CAR_{[-10, 10]}$	Cumulative market-adjusted stock return of the customer firm in the event window of [− 10, 10] days relative to the QEA of customers

Acknowledgements We thank C.-F. Lee (the Editor) and two anonymous reviewers. We appreciate helpful comments from Danqi Hu (discussant), Sudipta Basu, Rashad Abdel-Khalik, Jeffrey Callen, Tim Simin (discussant), and participants at 2020 AAA virtual Annual Meeting, Multinational Finance Society Conference in Jerusalem and 29th Annual Pacific Basin Finance, Economics, Accounting and Management Conference, and research seminar participants at Central University of Finance and Economics and Hang Seng University of Hong Kong. All coauthors have made equal contribution to the paper. Wenming Wang acknowledges the financial support from the Key Project of Philosophy and Social Sciences Research sponsored by Ministry of Education of China [No. 20JZD014]. Wenlan Zhang acknowledges financial support from the National Natural Science Foundation of China (No. 71702188). The authors alone are responsible for all limitations and errors that may relate to the paper.

References

Alldredge DM, Cicero DC (2015) Attentive insider trading. J Financ Econ 115(1):84–101

Asquith P, Meulbroek LK (1995) An empirical investigation of short interest: Division of Research, Harvard Business School

Asquith P, Pathak PA, Ritter JR (2005) Short interest, institutional ownership, and stock returns. J Financ Econ 78(2):243–276

Banerjee S, Dasgupta S, Kim Y (2008) Buyer-supplier relationships and the stakeholder theory of capital structure. J Financ 63(5):2507–2552

Bhattacharyya S, Nain A (2011) Horizontal acquisitions and buying power: a product market analysis. J Financ Econ 99(1):97–115

Boehmer E, Jones CM, Wu J, Zhang X (2020) What do short sellers know? Rev Finance 24(6):1203–1235

Brown S, Hillegeist SA, Lo K (2004) Conference calls and information asymmetry. J Account Econ 37(3):343–366

Bushee BJ (1998) The influence of institutional investors on myopic R&D investment behavior. Account Rev 73(3):305–333

Casciaro T, Piskorski MJ (2005) Power imbalance, mutual dependence, and constraint absorption: a closer look at resource dependence theory. Adm Sci Q 50(2):167–199

Cen L, Hertzel M, Schiller C (2017) Speed matters: limited attention and supply-chain information diffusion. Working Paper

Chen L, Zhang G, Zhang W (2016) Return predictability in the corporate bond market along the supply chain. J Financ Markets 29:66–86

Cheung Y, Haw I, Hu B, Swink M, Zhang W (2020) Common institutional investors and supplier performance in supply chains. J Oper Manag 66:670–696

Choy SK, Zhang H (2019) Public news announcements, short-sale restriction and informational efficienc. Rev Quant Financ Acc 52(1):197–229

Christophe SE, Ferri MG, Angel JJ (2004) Short-selling prior to earnings announcements. J Financ 59(4):1845–1876

Christophe SE, Ferri MG, Hsieh J (2010) Informed trading before analyst downgrades: evidence from short sellers. J Financ Econ 95:85–106

Cohen L, Frazzini A (2008) Economic links and predictable returns. J Financ 63(4):1977–2011

Dai R, Ng L, Zaiats N (2017) Do short sellers exploit news of related firms. Working Paper

Dechow PM, Hutton AP, Meulbroek L, Sloan RG (2001) Short-sellers, fundamental analysis, and stock returns. J Financ Econ 61(1):77–106

Desai H, Krishnamurthy S, Venkataraman K (2006) Do short sellers target firms with poor earnings quality? Evidence from earnings restatements. Rev Acc Stud 11(1):71–90

Diamond DW (1985) Optimal release of information by firms. J Financ 40(4):1071–1094

Diether KB, Lee K-H, Werner IM (2008) Short-sale strategies and return predictability. Rev Financ Stud 22(2):575–607

Dong MC, Liu Z, Yu Y, Zheng J-H (2015) Opportunism in distribution networks: the role of network embeddedness and dependence. Prod Oper Manag 24(10):1657–1670

Engelberg JE, Reed AV, Ringgenberg MC (2012) How are shorts informed: short sellers, news, and information processing. J Financ Econ 105(2):260–278

Fee CE, Thomas S (2004) Sources of gains in horizontal mergers: evidence from customer, supplier, and rival firms. J Financ Econ 74(3):423–460

Fee CE, Hadlock CJ, Thomas S (2006) Corporate equity ownership and the governance of product market relationships. J Financ 61(3):1217–1251

Geczy CC, Musto K, Reed AV (2002) Stocks are special too: an analysis of the equity lending market. J Financ Econ 66(2–3):241–269

Guan Y, Wong MF, Zhang Y (2015) Analyst following along the supply chain. Rev Acc Stud 20(1):210–241

Gong G, Luo S (2018) Lenders' experience with borrowers' major customers and the debt contracting demand for accounting conservatism. Account Rev 93(5):187–222

Hertzel MG, Li Z, Officer MS, Rodgers KJ (2008) Inter-firm linkages and the wealth effects of financial distress along the supply chain. J Financ Econ 87(2):374–387

Hui KW, Klasa S, Yeung PE (2012) Corporate suppliers and customers and accounting conservatism. J Account Econ 53(1):115–135

Intintoli VJ, Serfling M, Shaikh S (2017) CEO turnovers and disruptions in customer–supplier relationships. J Financ Quant Anal 52(6):2565–2610

Israeli D, Lee CM, Sridharan SA (2017) Is there a dark side to exchange traded funds? An information perspective. Rev Acc Stud 22(3):1048–1083
Kang J-K, Tham M, Zhu M (2012) Spillover effects of earnings restatements along the supply chain. Working Paper
Karpoff J, Lou X (2010) Short sellers and financial misconduct. J Financ 65:1879–1913
Khan M, Lu H (2013) Do short sellers front-run insider sales? Account Rev 88(5):1743–1768
Kim J-B, Song BY, Zhang Y (2015) Earnings performance of major customers and bank loan contracting with suppliers. J Bank Finance 59:384–398
Kolay M, Lemmon M, Tashjian E (2016) Spreading the misery? Sources of bankruptcy spillover in the supply chain. J Financ Quant Anal 51(6):1855–1990
Kot HW (2007) What determines the level of short-selling activity? Financ Manag 36(4):123–141
Kutsuna K, Smith JK, Smith R, Yamada K (2016) Supply-chain spillover effects of IPOs. J Bank Finance 64:150–168
Lee E (2016) Short selling and market mispricing. Rev Quant Financ Acc 47(3):797–833
Luo S, Nagarajan NJ (2015) Information complementarities and supply chain analysts. Account Rev 90(5):1995–2029
Madsen J (2017) Anticipated earnings announcements and the customer–supplier anomaly. J Account Res 55(3):709–741
Massoud N, Nandy D, Saunders A, Song K (2011) Do hedge funds trade on private information? Evidence from syndicated lending and short-selling. J Financ Econ 99(3):477–499
Menzly L, Ozbas O (2010) Market segmentation and cross-predictability of returns. J Financ 65:1555–1580
Moran P (2005) Structural vs. Relational embeddedness: social capital and managerial performance. Strat Manag J 26(12):1129–1151
Nagel S (2005) Short sales, institutional investors and the cross-section of stock returns. J Financ Econ 78(2):277–309
Pandit S, Wasley CE, Zach T (2011) Information externalities along the supply chain: the economic determinants of suppliers' stock price reaction to their customers' earnings announcements. Contemp Account Res 28(4):1304–1343
Pfeffer J, Salancik G (1978) The external control of organizations: a resource dependence perspective. Harper and Row, New York
Polidoro F Jr, Ahuja G, Mitchell W (2011) When the social structure overshadows competitive incentives: the effects of network embeddedness on joint venture dissolution. Acad Manag J 54(1):203–223
Richardson S (2003) Earnings quality and short sellers. Account Horiz 17:49–61
Safieddine A, Wilhelm WJ Jr (1996) An empirical investigation of short-selling activity prior to seasoned equity offerings. J Financ 51(2):729–749
Securities and Exchange Commission (2007) Economic analysis of the short sale price restrictions under the regulation sho pilot. Securities and Exchange Commission Working Paper
Shleifer A, Vishny RW (1997) The limits of arbitrage. J Financ 52(1):35–55
Stambaugh RF, Yu J, Yuan Y (2015) Arbitrage asymmetry and the idiosyncratic volatility puzzle. J Financ 70(5):1903–1948
Titman S (1984) The effect of capital structure on a firm's liquidation decision. J Financ Econ 13(1):137–151
Von Beschwitz B, Chuprinin O, Massa M (2017) Why do short sellers like qualitative news? J Financial Quant Anal 52(2):645–675
Yan XS, Zhang Z (2009) Institutional investors and equity returns: are short-term institutions better informed? Review of Financial Studies 22(2):893–924