Customer-Supplier Relationships and Abnormal Accruals

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ABSTRACT

We investigate the relationship between customer and supplier firms' abnormal accruals to examine whether the supply chain is an important transmission channel of abnormal accruals. We propose "earnings management" hypothesis and "customer demand shock" hypothesis. Empirically, we examine the relation between a supplier's estimated abnormal accruals and those of its major customers using Compustat Business Segment Files over the period 1987-2015. To further explore the demand shock channel, we directly test the impact of the bullwhip effect on the linkage in abnormal accruals along the supply chain. Following the literature in operation management, we construct the amplification ratio, measured as the coefficient of variation of a firm's orders divided by the coefficient of variation of the firm's demand. We find that customer firms' demand shocks link customer and supplier abnormal accruals as they propagate along the supply chain, via the "bullwhip" effect. Our evidence supports "customer demand shock" hypothesis. Consistent with the view that improving predictions on orders from their customers would mitigate this bullwhip effect, we find that a customer's abnormal accruals have a much smaller impact on those of its suppliers whose auditors have expertise in the customer's industries. Overall, our results suggest that the supply chain is an important transmission channel of abnormal accruals, and auditor expertise serves to reduce information opaqueness during this process. Our paper contributes to the literature examining the impact of bullwhip effects on firms' financial performance and the role of auditors' expertise in reducing information opaqueness in supply chain.

Keywords: *abnormal accruals; bullwhip effects; suppliers; customers.*

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1. Introduction

Given the complexity of modern production, firms have become increasingly connected through the supply chain. This network linkage not only facilitates the product and service flow from one firm to another, but also makes it possible for supply-chain connected firms to exert influence over one another's accounting and financial policies. The literature documents evidence that customer-supplier relationships significantly affect firm financing decisions (Banerjee, Dasgupta, and Kim, 2008; Kale and Shahrur 2007; Luo and Yu 2018; Chen and Liao 2018; Chen, Liao, and Huang 2014; Yu and Chen 2017), compensation decisions (Gu and Venkateswaran 2018), mergers and acquisitions (Ahern 2012; Ahern and Harford 2014; Baxamusa, Javaid, and Harery 2015), return predictability (Cohen and Frazzini 2008; Chen 2018), earning predictability (Eshleman and Guo 2014), accounting conservatism (Hui, Klasa, and Yeung 2012) and cash holdings (Itzkowitz 2012). Although these studies have recognized the importance of supply chain relationships, how firm abnormal accruals transmit along the supply chain is still an open question. This is an important question for two reasons. First, abnormal accruals are often interpreted as evidence that managers manipulate earnings. If abnormal accruals of firms transmit along the supply chain, then the effects of earnings management are not limited to the boundary of a firm. Rather, it will have ripple effects that cause accruals quality across such connected firms. Second, customer' accruals due to firm demand shocks are captured as abnormal accruals if the demand shocks are idiosyncratic for a customer firm, but not industry-wide or economy-wide. The demand shocks will transmit to suppliers, who anticipate changes in the future. Evidence that abnormal accruals of firms are connected via supply chain economics would suggest that related customer demand shocks drive some abnormal accruals, and such accruals are not merely determined by firms' own policies. Either way, studying abnormal accruals can provide new perspectives to the literature.

In this paper, we study how customer abnormal accruals affect those of suppliers. Consistent with our arguments above, we propose two hypotheses in the paper. The “earnings management” hypothesis predicts that abnormal accruals of suppliers and customers are negatively related. For example, if a customer firm intends to manipulate earnings upward by reducing the cost of inventory, its supplier’s accounts receivables would be squeezed to a smaller amount, which would translate into lower earnings for the supplier. Since the earnings management behavior at one customer firm is not expected to be an industry-wide phenomenon, the lower accounts receivables (and lower earnings) at the supplier firm imply lower abnormal accruals at the supplier firm. Thus, the “earnings management” hypothesis predicts that higher abnormal accruals at the customer firm associate with lower abnormal accruals at the supplier firm.

In contrast, the “customer demand shock” hypothesis predicts a positive relation between the abnormal accruals of customers and suppliers. Owens, Wu, and Zimmerman (2016) show that estimates of abnormal accruals reflect idiosyncratic differences in firms within an industry that are not captured by the industry linear regression models used in computing abnormal accruals. When a customer firm experiences a positive demand shock that is firm-specific, its suppliers naturally try to forecast changes to customer future demand of input goods and services by stocking up inventories of their own, for example. Since the demand shock to the customer firm is idiosyncratic and so is the ‘rippled’ shock to suppliers, industry regressions used to estimate abnormal accruals can’t capture idiosyncratic differences in firms, yielding a higher level of abnormal accruals at the supplier firms. According to the “customer demand shock’ hypothesis, therefore, customer abnormal accruals have a positive impact on those of suppliers.

Empirically, we examine the relation between a supplier’s estimated abnormal accruals and those of its major customers (firms that purchase more than 10% of the supplier’s aggregate sales).

We find that abnormal accruals of suppliers positively relate to the abnormal accruals of customers. This suggests that the demand shock channel dominates relative to the earnings management channel.

To further explore the demand shock channel we next examine if there is a "bullwhip" effect along the supply chain. First, we identify trios of firms linked via a supply chain. These trios include an ultimate customer (C), the supplier to the ultimate customer (S1), and the supplier to the supplier of the ultimate customer (S2): C→S1→S2. The "bullwhip" effect predicts that the connections between C and S1 will further magnify and affect S2 to an even greater extent. Consistent with the "bullwhip" effect, we document that the volatility of abnormal accruals economically and statistically increases from C to S1 to S2.

Second, we directly test the impact of the bullwhip effect (BWE) on the linkage in abnormal accruals along the supply chain. Following the literature in operation management, we construct the amplification ratio, measured as the coefficient of variation of a firm's orders divided by the coefficient of variation of the firm's demand (discussed in detail below). The presumption is that the larger is the bullwhip effect, the greater the resulting amplification ratio (Hammond 1994; Cachon, Randall, and Schmidt 2007; Wong, El-Beheiry, Johansen, and Hvolby 2007; Dong, Dresnera, and Yao 2011; Bray and Mendelson 2012). Consistent with the BWE, we find that the transmission of abnormal accruals from customers to suppliers is only significant when the amplification ratio is relatively high (above the sample median).

As mentioned above, one of the primary determinants of the BWE is the degree to which supplier firms have inferior information about the customer firm's demand. We corroborate this assertion using analyst forecast errors of customers' future EPS. We argue that customer-supplier asymmetric information is likely to be higher for those customer firms exhibiting greater analyst forecast errors. The presumption is that if the information processed by forecasting experts is more imprecise, the supplier's information about future customer demand is also likely to be more imprecise. This would arise if the supplier and the experts rely on the same information sources, or if the supplier relies directly on the experts' opinions. In support of the BWE, we find that the magnitude of the relationship between customer and supplier abnormal accruals increases with the magnitude of customer firm analyst forecast error.

The bullwhip effect may be mitigated by implementing processes that reduce information asymmetry, such as information sharing between suppliers and customers, better forecasting models and improved ordering policies (Lee, Padmanabhan, and Whang 1997; Geary, Disney, and Towill 2006; Duc, Luong, and Kim 2010). However, there is little evidence in the literature addressing the role of information intermediaries, such as auditors, in mitigating BWE. Auditors may have valuable information on customers' industries, and such knowledge may benefit supplier firms in aligning production with demand. For example, the information on downstream replenish policy is valuable in improving upstream order fulfillment forecast accuracy (Cui, Allon, Bassamboo, and Mieghem 2015).

We next examine if auditor expertise can attenuate the bullwhip effect. It has been well documented in the accounting literature that auditor expertise can provide firms with useful information. We explore whether the supplier's auditor's expertise *in the customer's industry* reduces the supplier's information imprecision. We find that the supplier's abnormal accruals are less responsive to (i.e., are less magnified by) customer abnormal accruals when its auditors have expertise in the customer's industry. This finding suggests that auditor expertise attenuates information asymmetry about customer demand shocks and helps mitigate the bullwhip effect.

To confirm the abnormal accruals relationship, we examine whether the relationship between customers and suppliers is spurious and/or whether it may be driven by factors other than the supply chain. As a robustness check, we conduct placebo tests using noncustomer firms of similar size in a same industry (as measured by 2-digit SIC codes). Given that sampled customers tend to be larger than suppliers, one could argue that the customer-supplier abnormal accruals relationship is simply due to this size factor of customers rather than to the supply-chain effect. To address this concern, we randomly assign a non-customer firm in the same industry (as measured by 2-digit SIC codes) and size decile (as measured by assets) as an “artificial” customer firm. We then substitute this ‘randomly-assigned’ customer for the supplier’s actual customer. In this artificially constructed customer-supplier pair sample, there is no actual supply-chain relationship, but the size and industry factors remain. We rerun our tests using this artificial sample and find that the artificial customers’ abnormal accruals have no effect on the suppliers’ abnormal accruals. This result rules out the size effect and lends strong support to the supply chain argument in interpreting our results.

Our results suggest that a supplier’s abnormal accruals are significantly affected by those of its customers. In other words, a firm’s abnormal accruals are determined not only by firm and industry characteristics, but also by the characteristics of supply chain related firms.

Our contributions are threefold. First, our findings complement those of Owens, Wu, and Zimmerman (2016), who find that abnormal accruals reflect firm-specific fundamentals and demand shocks. Our study suggests that these effects not only influence a firm’s own abnormal accruals but also the abnormal accruals of firms along a supply chain. To our knowledge, our paper is the first to directly examine the “bullwhip” effect in firm accruals. Second, we also contribute to the growing body of research investigating the influence of customer-supplier relationships on firms' decisions and outcomes, such as strategic relationship investments (Kale and Shahrur 2007; Luo and Yu 2018), credit risk (Campello and Gao 2016), cash holding (Itzkowitz 2013), contagion effects along a supply chain including financial distress (Hertzel, Li, Officer, and Rodgers 2008), financing decisions (Johnson, Kang, Masulis, and Yi 2014), return predictability (Cohen and Frazzini 2008), and the effect of customer-base concentration on corporate public disclosure policy (Crawford, Huang, Li, and Yang 2016). Third, our paper contributes to the literature examining the role of auditor expertise. Reichelt and Wang (2010) provide evidence that auditors with expertise provide better audit quality, as measured by lower levels of abnormal accruals and smaller likelihood of meeting or beating analyst forecasts by one penny per share at client firms. Our findings suggest auditor expertise helps reduce information asymmetry among supply-chain related firms, and thus can mitigate the bullwhip effects on abnormal accruals.

2. Hypothesis Development

Accruals play an integral part in filling the gap between earnings and cash flow recognition. They are important for understanding firm performance metrics (Dechow 1994). Yet their estimation often involves subjectivity and may be subject to unintentional mismeasurement (Richardson, Sloan, Soliman, and Tuna 2005) and intentional manipulation (Sloan 1996; Xie 2001; Dechow, Ge, and Schrand 2010). Research investigating earning management typically separates total accruals into normal and abnormal components, where abnormal accruals intend to capture the discretionary component of accruals and are empirically estimated by industry-level regressions with a firm's own characteristic variables. As pointed out by Owens et al. (2016), this type of estimation assumes that firms' accrual-generating processes are relatively stable (i.e., firm stationarity), and that industry peers have similar accrual-generating processes (i.e. intra-industry homogeneity). However, even within the same industry, firms would react to the same demand shock differently. Simply put, idiosyncratic demand shocks and nonlinear economic forces along a supply chain will be empirically captured by abnormal accruals in the current accrual models.

We begin by motivating the "earnings management" hypothesis that predicts that abnormal accruals of suppliers and customers are negatively related. If customer firms manipulate earnings upward by reducing the cost of inventory, then their supplier's accounts receivables will be mechanically pushed downward, resulting in lower earnings for the supplier. Since the earnings management behavior for a single customer firm is unlikely to be an industry-wide phenomenon, the lower accounts receivables (and lower earnings) at the supplier firm will result in lower abnormal accruals for the supplier firm. Thus, the "earnings management" hypothesis predicts that higher abnormal accruals at the customer firm associate with lower abnormal accruals at the supplier firm.

> **H1A**: *Ceteris paribus, estimated abnormal accruals of a supplier are negatively associated with abnormal accruals of a major customer.*

A supplier's accruals naturally link to those of its customers' through the supply chain. Consider a positive shock to the demand for a firm's products, leading the firm to increase its accruals. This demand shock reverberates up the supply chain as the firm increases its demand for input goods from its suppliers. The result will be an increase in the supplier's accruals that are likely proportional to those of its customer (the firm experiencing the initial shock) as both firms experience increased production and profitability stemming from the common variation in product demand.

If changes in demand are industry or economy-wide, the effects will be felt by all suppliers in the same industry and will be captured in normal accruals. Alternatively, if the demand changes are (partially) idiosyncratic, only the specific suppliers of the shocked firm will be affected. Given that normal/abnormal accruals are measured relative to an industry-wide benchmark, positive idiosyncratic demand innovations to customer firms will lead to increased abnormal accruals for their suppliers. The same will be true for the reverse: a negative idiosyncratic demand innovation for the customer's products will decrease its abnormal accruals and those of its suppliers. Specifically, given the lead-lag relationship between inventory ordering and revenue recognition, the effects of demand shocks will not be fully captured by revenue and will show up in abnormal accruals. For example, assume a supplier firm observes that a customer firm has a positive demand shock for the customer's goods. To prepare for the future orders anticipated to come from the customer firm, the supplier firm orders more inventory from its suppliers. Supplier firm revenue will not recognize/reflect the shock until that inventory is sold, so total accruals increase (from the inventory order) but that increase is not explained by the concurrent revenue (i.e., the effect of the shock on revenue will come once the new inventory is sold to the customer firm). As a result, the shock causes positive abnormal accruals for the supplier firm. This is a phenomenon will occur upstream and downstream in the supply chain creating a positive correlation among the abnormal accruals of the related firms. This argument indicates a positive relationship between the abnormal accruals of a powerful customer and the less powerful supplier of a customer. We develop the "customer demand shock" hypothesis below:

H1B: *Ceteris paribus, estimated abnormal accruals of a supplier are positively associated with abnormal accruals of a major customer.*

We know from the supply-chain literature that changes in the demand for a customer's products will magnify as they transmit to its supplier and the supplier to the customer's supplier. For example, consider a smartphone manufacturer that experiences increased retail demand. It will need to produce more smartphones and will increase the orders for parts from suppliers. These suppliers in turn will also need to order more input materials from their suppliers. Thus, the increased demand for smartphones will reverberate up the supply chain in what the supply-chain literature calls "the bullwhip effect". The bullwhip effect refers to the notion that small changes in the demand for smartphones will lead to larger effects upstream. This magnification can occur as a result of order batching (where orders are made in batches and only crudely communicate fluid demand changes), accumulation of safety stock, and/or price variation. Moreover, the size of suppliers relative to their customers makes a common-sized demand shock relatively large as it progresses up the supply chain (to typically smaller and smaller firms) (see Forrester 1961, Lee et al. 1997, and Bray and Mendelson 2012). Based on these arguments, we hypothesize in the context of abnormal accruals that:

> **H2A**: *Ceteris paribus, the volatility of abnormal accruals of a supplier's supplier is higher than the volatility of abnormal accruals of its major customer.*
>
> **H2B**: *Ceteris paribus, abnormal accruals of a supplier are positively associated with abnormal accruals of its major customer when the bullwhip effect arises.*

The bullwhip effect arises because the supplier firms can't perfectly forecast the customer's demand shocks or the resulting new orders, due to information asymmetry. The further upstream a supplier firm is in the supply chain, the more opaque the information, thus the less precise any forecasts the supplier firm may come up with. This information asymmetry argument has two implications. First, if customer-supplier information asymmetry is higher for those customer firms with greater analyst forecast error, which could arise either because the suppliers and analysts rely on the same sources of information, or because the suppliers directly use analysts' opinions, we would see a stronger impact of customer abnormal accruals on those of suppliers where customer firms have greater analyst forecast error. Second, information intermediaries that reduce information asymmetry would mitigate the relationship between customer and supplier abnormal accruals. Specifically, we look at auditors that are experts in the customer's industry. Auditors, as information intermediaries, can reduce information asymmetry by helping suppliers better predict customer demand shocks. Based on these arguments, we propose the following:

> **H3**: *Ceteris paribus, estimated abnormal accruals of a supplier will be even more positively associated with abnormal accruals of its major customer in firms with greater analyst forecast error.*

> **H4**: *Ceteris paribus, estimated abnormal accruals of a supplier will be less positively associated with abnormal accruals of its major customer if its auditor has expertise in the customer's industry.*

3. Sample Selection and Research Design

3.1 *Sample selection*

To identify firms connected by supply chains, we use Compustat Business Segment Files over the period 1987-2015. Compustat Business Segment Files report the names of a firm's customers when they account for at least 10% of the firm's sales (i.e., "major customers")[1]. One challenge in dealing with this dataset is that there is no customer ID. We have to manually match a customer by its full name (and sometimes abbreviation) to the corresponding record on Compustat in order to obtain financial information for the customer (Ellis, Fee, and Thomas 2012). For customer firms that we were unsure of by name, we probed further by examining industry affiliations and searching for possible websites for those companies. Any customer names that could not be clearly matched were excluded from our sample to ensure accuracy.

[1] SFAS 14 requires that public firms disclose customers that account for at least 10 percent of their total sales.

We focus on the largest customer of a supplier, which has the largest reported share of the supplier's sales in a given year. We choose to use the largest customer because it is likely to have more pronounced effects on its supplier as well as greater bargaining power over its supplier. This helps alleviate concerns of reverse causality (i.e., that the supplier drives customer accruals rather than the other way around). We require firms to have non-missing abnormal accruals and other control variables.

After imposing these data requirements and removing data errors, we ended up with a sample of 15,252 firm-year observations on 3,458 unique nonfinancial supplier firms (i.e., excluding firms with SIC codes 6000-6999) from 1987 to 2015 for tests on abnormal accruals. Table 1 Panel A details our data screening process. This sample consists of all firms with non-missing variables in the regressions designed to test H1A and H1B. To further examine the transmission of abnormal accruals among customers, suppliers and the suppliers' suppliers (H2A), we form a subsample consisting of trios of firms linked via supply chains. This sample has 1,212 unique trios of customer – 1st supplier – 2nd supplier (C-S1-S2) relationships.

3.2 *Research design*

3.2.1 *Abnormal accruals measures*

We measure abnormal accruals following the prior accounting literature. We first measure total accruals taken directly from cash flow statements. Hribar and Collins (2002) conclude that total accruals calculated from the statement of cash flows alleviate the errors-in-variables problem due to non-articulated changes related to non-operating events.

$$TA_{i,t} = EBXI_{i,t} - CFO_{i,t} \quad (1)$$

where $TA_{i,t}$ is total accruals in year *t* for firm *i*, $EBXI_{i,t}$ is the earnings before extraordinary items and discontinued operations in year *t* for firm *i* and $CFO_{i,t}$ is the operating cash flows (from continuing operations) taken from the statement of cash flows in year *t* for firm *i*.

To obtain abnormal accruals, we follow Jones (1991) and estimate cross-sectional regressions of abnormal accruals by year for each 2-digit SIC industry:

$$\frac{TA_{i,t}}{A_{i,t-1}} = \alpha_{0,i}\left(\frac{1}{A_{i,t-1}}\right) + \alpha_{1,i}\frac{\Delta REV_{i,t}}{A_{i,t-1}} + \alpha_{2,i}\frac{PPE_{i,t}}{A_{i,t-1}} + \varepsilon_{i,t} \quad (2)$$

where $TA_{i,t}$ = total accruals in year *t* for firm *i*; $\Delta REV_{i,t}$= revenues in year *t* less revenues in year *t-1* for firm *i*; $PPE_{i,t}$= gross property, plant, and equipment in year *t* for firm *i*; and $A_{i,t-1}$= total assets in year *t-1* for firm *i*. In Eq. (2), gross property, plant and equipment (PPE) and change in revenues (ΔREV) are included in the expectations model to control for changes in accruals caused by the changing conditions of business operations.

We then use parameter estimates from Eq. (2) and the sample firm's own data to construct estimates of firm-specific normal accruals (*NA_J*) and abnormal accruals (*AA_J*):

$$NA\_J_{i,t} = \hat{\alpha}_{0,i}\left(\frac{1}{A_{i,t-1}}\right) + \hat{\alpha}_{1,i}\frac{\Delta REV_{i,t}}{A_{i,t-1}} + \hat{\alpha}_{2,i}\frac{PPE_{i,t}}{A_{i,t-1}}, \quad (3)$$

$$AA\_J_{i,t\_} = \frac{TA_{i,t}}{A_{i,t-1}} - NA_{J_{i,t}}, \quad (4)$$

where our measure of abnormal accruals ($AA\_J_{i,t}$) is the difference between total accruals ($TA_{i,t}$) and normal accruals ($NA\_J_{i,t}$). We also estimate two alternative abnormal accruals based on a modified Jones model (Dechow et al. 1995) (*AA_MJ*) and a model controlling for ROA, as in Holthausen et al. (1995) and Kothari et al. (2005), who suggest controlling for the normal level of accruals conditional on ROA (we label this measure as *AA_PMJ*). We discuss the methods used to construct these alternative measures of abnormal accruals in Appendix A.

Using these estimates of abnormal accruals, we test whether abnormal accruals of a given supplier relate to the abnormal accruals of its largest customer:

$$S\_AA_{i,t} = \beta_0 + \beta_1 C\_AA_{i,t} + \sum \beta_j Controls_{j,i,t} + \mu_{i,t}, \quad (5)$$

where $S\_AA_{i,t}$ is the abnormal accruals of the supplier, and $C\_AA_{i,t}$ is the abnormal accruals of the supplier's largest customer. These measures are computed using the three measures of abnormal accruals described earlier. "*i*" indexes the firm. "*j*" indexes the *j*th control variable for *j*>2. "*t*" indexes the year. According to H1A (H1B and H2B), we expect the coefficient on *C_AA* (β_1) to be negative (positive) for a relationship due to earnings management (demand shocks). Control variables include other incentives for earnings management documented in the prior literature, such as variables capturing the future need to tap into the equity markets and debt markets, and firm characteristics, such as total assets, firm age since IPO, sales growth, whether the auditor is a big eight auditor, operating cash flow, leverage, and market-to-book value. We also include customer's R & D and supplier's R & D in regressions to control for customer's R&D investment in partner relationships (Raman and Shahrur 2008). Panel regressions include year- and industry-fixed effects, and we report robust standard errors clustered by firm.

3.2.2 *Measuring the bullwhip effect*

Following Hammond (1994), we measure the bullwhip effect with the amplification ratio (*AMP RATIO)* defined as the coefficient of variation of outgoing orders divided by the coefficient of variation of incoming orders. Outgoing orders and incoming orders capture production and demand, respectively. We measure demand (D_t) with cost of goods sold (COGS) and production

(O_{it}) with the difference between change in inventory from year *t* to year *t+1* and COGS (Cachon et al. 2007; Wong et al. 2007; Dong et al. 2011; Bray and Mendelson 2012). Following Bray and Mendelson (2012), we convert inventory value for observations with FIFO to LIFO by adding the LIFO reserve to inventory, and adjusting COGS with the change in LIFO reserve to keep consistency in the inventory method.

$$O_{it} = inventory_t - inventory_{t-1} + D_t \quad (6)$$

$$CV_O = \sigma(\frac{O_{it}}{AT_{it}}, \frac{O_{it-1}}{AT_{it-1}}, \frac{O_{it-2}}{AT_{it-2}}) / \mu(\frac{O_{it}}{AT_{it}}, \frac{O_{it-1}}{AT_{it-1}}, \frac{O_{it-2}}{AT_{it-2}}) \quad (7)$$

$$CV_D = \sigma(\frac{D_{it}}{AT_{it}}, \frac{D_{it-1}}{AT_{it-1}}, \frac{D_{it-2}}{AT_{it-2}}) / \mu(\frac{D_{it}}{AT_{it}}, \frac{D_{it-1}}{AT_{it-1}}, \frac{D_{it-2}}{AT_{it-2}}) \quad (8)$$

$$AMP\ RATIO = {}^{CV_O}/_{CV_D} \quad (9)$$

Consistent with Hammond (1994), we consider the bullwhip effect present when the *AMP RATIO* is greater than one. To test H2B, we split the sample into two subsamples: one for an *AMP RATIO* greater than one and another one for an *AMP RATIO* less than one. If the bullwhip effect is the presumed condition for the linkage in abnormal accruals of a supplier and its customer, we would observe the link only holds for the subsample of *AMP RATIO* greater than one.

4. Results Analysis

4.1 *Sample characteristics*

In Panel B of Table 1, we present univariate statistics for our sample used to test H1A and H1B. All variables are defined in Appendix B. Comparing the mean market capitalization of customers (*C_MV*) and that of suppliers (*S_MV*), *C_MV* is much larger than that of suppliers: $56.8 billion versus $2.6 billion. The median ratio of their market capitalizations - major customers' over suppliers' (*C_MV/S_MV*) - indicates that median customers are 105 times larger than suppliers.

The 25th percentile of this ratio is 16, suggesting that major customers are much larger than suppliers for the majority of the sample. Relative size based on total assets shows a similar pattern. The statistics on sizes indicate that major customers are more powerful compared to suppliers.

Table 1 Panel B also reports the accrual measures for both customers and suppliers. The average Jones (1991) abnormal accruals for customers *C_AA_J* (suppliers *S_AA_J*) is -0.01 (-0.02). The average modified Jones abnormal accruals for customers *C_AA_MJ* (suppliers *S_AA_MJ*) is -0.01 (-0.02). The average modified Jones abnormal accruals controlling for customer ROA *C_AA_PMJ* (suppliers *S_AA_PMJ*) is -0.02 (-0.02).

Turning to firm characteristics in Panel B of Table 1, we find that the average supplier annual sale growth (*SALEGR*), leverage (*LEV*), *R & D*, and book-to-market value (*B2M*) are 15%, 19.6%, 6.7% and 2.78, respectively. Most of the auditors of suppliers rank as top 8 auditors: 79%. Regarding incentives to tap into the capital markets, the descriptive statistics show that the average estimates of debt issuance and equity issuance are positive and equal to 3% and 19% of assets, respectively. However, both medians are 0, suggesting that most firms are not actively raising capital in most years. Panel B also reports descriptive statistics for customer firm characteristics used in our regression analyses. The average customer sales growth rate is 11.2%. The R & D spending for customers on average are 3.7%. The average changes in inventories and accounts payables from year t-1 to year t are both around 2% of assets.

Panel C and Panel D of Table 1 report the industry distribution of our sample for customers and suppliers, respectively. We see suppliers are concentrated in the *food*, *beverage* and *chemicals* and *plastics*, *computer* and *machinery* industries (1-digit SIC = 2 and 3, respectively), which combine to represent more than 72% of the sample. We also see that agriculture and public administrative services have the smallest presence at only 0.07% and 0.05% of the sample. Similar to suppliers, customers in our sample are concentrated in the *food*, *beverage* and *chemicals* and *plastics, computer* and *machinery* industries (1-digit SIC=2 and 3, respectively), but they also have a significant presence in the wholesale and retail industry (1-digit SIC=5). Customers from the agriculture industry (1 digit SIC=0), the finance, insurance, real estate industry (1-digit SIC=6) and the healthcare, professional and education services (1 digit SIC=8) are less common[2].

{Table 1 inserted here}

4.2 *The relationship between customer and supplier abnormal accruals*

We next explore the relationship between the abnormal accruals of suppliers and customers. Results are reported in Table 2. Model 1 tests H1A and H1B, where the suppliers' abnormal accruals are regressed on the customers' abnormal accruals. H1A and H1B predict that earnings management and idiosyncratic customer demand shocks will link together customer and supplier abnormal accruals. We find a large positive coefficient (0.050), statistically significant at the 1 percent level for abnormal accruals estimated based on the Jones (1991) model in Model 1. This finding does not support H1A but strongly supports H1B: abnormal accruals of a supplier are positively related to those of its major customer.

We further check the robustness of our results using accrual measures based on the modified Jones model (in Model 2) and the performance-based modified Jones model (in Model 3). Results are similar to what we find in Model 1. Overall, Table 2 provides strong evidence for our conjecture that idiosyncratic shocks to customers can transmit to suppliers through the supply

[2] We remove suppliers from the finance, insurance and real estate industry in our sample construction, but we do not impose the same criterion on customer firms. A finance firm that purchases technical services from a supplier, for example, can still be in our sample.

chain, leading to an economic linkage between suppliers' and customers' abnormal accruals. Coefficients on suppliers' firm characteristics are consistent with previous studies.

{Table 2 inserted here}

4.3 *Two-step regressions of customer-supplier abnormal accruals*

To alleviate concerns that the customer-supplier abnormal accruals relationship is spurious, in Table 3, we re-run Model 1 in Table 2 using a two-step process. In the first step, we attempt to identify variations in *C_AA_J* driven by economic factors that likely pass up the supply chain. We choose customers' sales growth, customers' changes in inventories, customers' changes in accounts payables, and customers' R & D expense for this step. These customer-specific factors likely drive the customers' abnormal accruals. We obtain the predicted value of customer abnormal accruals in this first step (*C_AA_J^HAT*) and then use this variable in place of *C_AA_J* in the second-stage regression. By doing so, we isolate the component of *C_AA_J* that is driven by its major customer due to the supply-chain effect from other drivers of *C_AA_J* due to non-supply-chain factors, such as accounting choices or managerial decisions. If the relationship between abnormal accruals we document in Table 2 is truly driven by supply-chain linkages, we expect an even stronger link between *C_AA_J* and *S_AA_J* using the predicted value of *C_AA_J* *(C_AA_J^HAT),* as the latter better captures the supply chain component of *C_AA_J*.

Results are reported in Table 3. Model 1 is the first-step prediction model for customer abnormal accruals based on the 1991 Jones specifications. Note that all three variables used in the regressions are highly significant. We then re-run Model 1 of Table 2 using the predicted value of *C_AA_J* (*C_AA_J^HAT*). As shown in Model 2 of Table 3, *C_AA_J^HAT* has a large positive coefficient, consistent with the results in Model 1 of Table 2. More interestingly, comparing the magnitudes of the coefficients, *C_AA_J^HAT* has a much bigger regression coefficient of 0.09, more than double its counterpart in Model 1 of Table 2 (0.050). This finding lends further support to the supply-chain effect we document between customer-supplier abnormal accruals. Regressions using the modified Jones model and the performance-based modified model yield similar results in Model 2 and 3 of Table 2.

{Table 3 inserted here}

4.4 *Bullwhip effect demonstrated by the volatility of abnormal accruals along the supply chain and AMP_RATIO*

Hypothesis H2A and H2B suggest that a customer's abnormal accruals will not only affect its supplier, but also the supplier of its supplier. First, we explore this "bullwhip" effect by identifying trios of firms linked via the supply chain, as reported in Table 4. We identify such trios as having a customer firm (C) which lacks any major customers itself; where C is identified as a major customer to its supplier (S1); and where S1 is identified as a major customer to its suppliers (S2). The resulting trio of firms represents a two-link supply chain starting with C and transmitting to S1 and S2: C→S1→S2. The bullwhip effect predicts that demand shocks originating at the ultimate customer firm will be less predictable for suppliers, resulting in abnormal accruals that magnify along the supply chain. This suggests that the volatility of abnormal accruals will increase as we travel from C to S1 to S2 firms.

Table 4 shows the standard deviation of abnormal accruals for the three sets of firms. For all three measures of abnormal accruals, we find that the standard deviation of abnormal accruals

S2_AA_J (*S2_AA_MJ* and *S2_AA_PMJ*) is the largest for S2 firms at 0.13 (0.13 and 0.11), smaller for S1 firms at 0.09 (0.09 and 0.07), and the smallest for C firms at 0.08 (0.08 and 0.07). Moreover these differences are statistically significant at the 1% level. This is precisely what one would predict from the bullwhip effect. Overall, these results support H2A and help illustrate the importance of supply-chain relationships in transmitting abnormal accruals up the supply chain.

{Table 4 inserted here}

We further directly test the impacts of bullwhip effects on the relationship between abnormal accruals along supply chains. Table 5 Panel A reports the descriptive statistics for *AMP_RATIO*. The mean (median) of *AMP_RATIO* is 1.17 (1.00). *AMP_RATIO* ranges from 0.22 to 5.49 with the standard deviation of 0.72. In Table 5 Panel B, we repeat tests on abnormal accruals along a supply chain reported in Table 2 for two subsamples: one for *AMP RATIO* greater than one and another for an *AMP RATIO* less than one as one is the median of the sample. If the link in abnormal accruals between a supplier and its major customer is caused by the bullwhip effect, we would expect the link only holds when the bullwhip effect is present. Upstream suppliers may face amplified outgoing orders compared to real demand from downstream customers if upstream suppliers distort the information on demand. The bullwhip effect refers to the amplification in demand variability along the supply chain from downstream customer firm to upstream supplier firm. Model 1 and Model 2 in Table 5 Panel B show the regressions of abnormal accruals estimated from the Jones model for the sample when the amplification ratio is less than one and the one when the amplification ratio is greater than one (i.e., when the bullwhip effect is present), respectively. The abnormal accruals of a customer no longer relate to those of its supplier for the sample when the amplification ratio is less than one, whereas the link in abnormal accruals of a supplier and its customer is robust for the sample when the amplification ratio is greater than one. The difference in the coefficients on abnormal accruals of customers measured with Jones model between the two subsamples in the Model 1 and Model 2 of Table 5 Panel B is 0.091 and significant at 10 percent level for chi-square tests. These results indicate an amplified transmission in demand variability from a customer to its upstream supplier through abnormal accruals, which is consistent with H2B. We find the results for the abnormal accruals estimated from the modified Jones and performance-based modified Jones model strongly support H2B as well. The difference in the coefficients on abnormal accruals of customers measured with the modified Jones model (performance-based modified Jones model) in the Model 3 and Model 4 (Model 5 and Model 6) of Table 5 Panel B is 0.05 (0.026) and significant at 10 percent (5 percent) level.

{Table 5 inserted here}

4.5 *The effect of analyst forecast error*

Hypothesis H3A highlights the role of information asymmetry in the abnormal accruals relation we document for customer and supplier firms. It is likely that customer firms with greater analyst forecast error make it particularly difficult for supplier firms to forecast changes in future new orders. As argued above, if the information processed by forecasting experts is imprecise, the supplier's information about future customer demand is also likely to be more imprecise, leading to a stronger relationship between customer-supplier abnormal accruals. We test H3 in Table 6.

In Table 6, we also interact customer abnormal accruals with analyst forecast error about the customer EPS. Analyst forecast error of a customer firm is defined as the absolute value of the difference between mean (median) consensus forecast of the customer firm's EPS and the customer firm's actual EPS divided by the customer firm's stock price at the end of the fiscal year.

In all model specifications, customer abnormal accruals (*C_AA_J(MJ,PMJ)*) have a positive impact on those of suppliers, consistent with results in Table 2. More importantly for this part of the test, the interaction term of customer abnormal accruals and customer firm analyst EPS forecast error (*INCR_AYST_ERR*) is significant and positive, indicating that the abnormal accruals of a customer firm with greater information asymmetry (i.e. analyst forecast error) have an even larger impact on those of its suppliers. This finding lends strong support to H3.

{Table 6 inserted here}

4.6 *The effect of auditor expertise*

We argue in H4 that auditor expertise may help suppliers better prepare for changes in future orders from a customer after it experiences a demand shock. In particular, if the auditor has expertise in the customer's industry, it can help the supplier estimate the customer demand shock better. It can also assist when the supplier needs to adjust accruals-related activities in preparation for the customer demand shock. Auditors' service reduces information asymmetry between customers and suppliers, and thus is expected to mitigate the impact of customer abnormal accruals on those of suppliers as the customer demand shocks vibrate up the supply chain.

In Table 7, we empirically examine the role of auditor expertise. In Model 1-3, we construct measures for auditor expertise in the customers' industries. Following Reichelt and Wang (2010), we measure *AUD_IND_EXP* as a dummy variable equal to one if the annual market share (i.e. audit fees) of the supplier's auditor is ranked in the top quintile in the customers' industry (based on 2-digit SIC codes) in a particular geographic city, and zero otherwise. We focus on the interaction term between the customer's abnormal accruals and *AUD_IND_EXP*. If the supplier's auditor's expertise in the customer's industry helps the supplier better predict the demand shocks of the customer, we expect to see a negative coefficient of this interaction term, which would suggest a mitigating effect from auditor expertise. As evident in Model 1-3, the customer's abnormal accruals interacted with supplier auditor expertise in the customer's industry exhibit a consistently negative coefficient, significant at the 5 percent level. Results in Table 7 suggest that auditors, as information intermediaries, help reduce information asymmetry along the supply chain, leading to a mitigated effect from customer abnormal accruals on those of suppliers.

{Table 7 inserted here}

4.7 *Placebo tests using matched non-customer Firms*

So far we have documented a consistent relationship between a customer's abnormal accruals and those of its suppliers. Building on the arguments by Owens et al. (2016), we interpret our findings as supporting the notion that idiosyncratic shocks to customer firms transmit along the supply chain through abnormal accruals, resulting in a positive impact from a customer's abnormal accruals on those of its supplier. In this section, we conduct some robustness tests to rule out other possible interpretations of our results.

Table 1 Panel B shows that customer firms in our sample are considerably larger relative to supplier firms. One possible explanation of our findings is that customer firms influence supplier accruals policies simply due to their big size and power, not necessarily due to the supply chain connection.

To examine whether the size effect or the supply chain effect drives our findings, we use an artificially constructed sample that removes the supply chain relationship between customers and suppliers but keeps the size characteristics of the customers. Specifically, we replace each customer in a customer-supplier pair in our sample with a randomly assigned non-customer firm, with the following requirements. First, the non-customer firm must come from the same industry as the customer firm, as measured by 2-digit SIC codes. Second, the non-customer firm and the customer firm belong to the same size decile in a given year, as measured by book assets. In doing so, we obtain an artificial sample where the paired non-customer and supplier firms have no supply chain connection, and by construction, the non-customer firms are similar to customer firms in terms of size and industry.

We re-run our regressions of supplier abnormal accruals on those of the non-customers'. If the customer size factor drives our results, we should continue to observe a significant relationship between the abnormal accruals of the non-customer firms and those of their matched suppliers. In contrast, if the supply chain effect explains our results, we should not observe any association between the abnormal accruals in this artificial sample, as the supply-chain relationship is absent by sample construction.

Results are reported in Table 8. As evident in Model 1-3, the non-customer firms are found to have no impact on suppliers' abnormal accruals. In other words, when the supply-chain relationship is absent, firms that are similar in size and industry to a supplier's actual customers have no effect on that supplier's abnormal accruals. This evidence supports the interpretation that the supply chain relationships drive our results.

To reinforce this point, in Model 4-6, we substitute back the suppliers' *actual* customers and re-run the regressions of the suppliers' abnormal accruals on their *actual* customers' abnormal accruals. Consistent with Table 2, and in contrast to Model 1-3 in Table 8, there are significant and positive coefficients on all of the actual customers' abnormal accruals measures. This finding lends further support to the supply chain interpretation of our results.

{Table 8 inserted here}

5. Conclusion

We investigate the impact of abnormal accruals of a major customer on those of its supplier. We argue that as customer firms experience demand shocks and adjust their accruals, suppliers also adjust theirs in attempt to forecast customer future orders for input goods and services. This adjustment in accruals is (partially) captured as abnormal accruals and is likely to ripple through the supply chain from downstream customer firms to affect other suppliers further up the supply chain.

Empirically, using industry-level regressions and controlling for firms' own characteristics to estimate abnormal accruals, we find strong support for the positive relationship between abnormal accruals of largest customers and their suppliers. This finding suggests that abnormal accruals based on current accrual models have a supply-chain component that are important but not yet accounted for.

Next, we test and empirically show that the influence from customer abnormal accruals on supplier abnormal accruals magnifies along the supply chain, from a supplier's major customer to the supplier and further from the supplier to its supplier, consistent with the so-called bullwhip effect. While the bullwhip effect is not new in the management literature, we are the first to demonstrate its existence in firm accruals policies.

Since the bullwhip effect is likely an outcome of information asymmetry as upstream suppliers forecast future customer demand using noisy information, we next investigate the role of auditors in reducing information asymmetry along the supply chain. We find that when suppliers' auditors have expertise in customer industries, the effect of customer abnormal accruals on those of suppliers is considerably weaker.

We further conduct robustness tests to rule out alternative explanations of our findings including the size effect. In short, our results suggest that the supply chain is an important transmission channel of abnormal accruals.

Appendix A: Alternative Measurements of Earnings Management Variables

We use Eq. (10), (11) and (12) to estimate the Modified Jones 1991 abnormal accruals (Dechow, et al. 1995). The *AA_MJ* is the difference between firm-level total accruals and fitted normal accruals at the industry-year level with adjustment of changes in accounts receivable in the regression for normal accruals.

$$\frac{TA_{i,t}}{A_{i,t-1}} = \alpha_{0,i}\left(\frac{1}{A_{i,t-1}}\right) + \alpha_{1,i}\frac{\Delta REV_{i,t}-\Delta REC_{i,t}}{A_{i,t-1}} + \alpha_{2,i}\frac{PPE_{i,t}}{A_{i,t-1}} + \varepsilon_{i,t}, \tag{10}$$

$$NA\_MJ_{i,t} = \hat{\alpha}_{0,i}\left(\frac{1}{A_{i,t-1}}\right) + \hat{\alpha}_{1,i}\frac{\Delta REV_{i,t}-\Delta REC_{i,t}}{A_{i,t-1}} + \hat{\alpha}_{2,i}\frac{PPE_{i,t}}{A_{i,t-1}}, \tag{11}$$

$$AA\_MJ_{i,t\_} = \frac{TA_{i,t}}{A_{i,t-1}} - NA\_MJ_{i,t}, \tag{12}$$

Where Δ*REC* is the change in accounts receivable from year *t-1* to year *t* for firm *i*.

We use Eq. (13), (14) and (15) to estimate the modified Jones model controlling for ROA, a.k.a. performance-based modified Jones model (Kothari et al. 2005). The *AA_PMJ* is the difference between firm-level total accruals and fitted normal accruals at the industry-year level with *ROA* in the regression for normal accruals.

$$\frac{TA_{i,t}}{A_{i,t-1}} = \alpha_{0,i}\left(\frac{1}{A_{i,t-1}}\right) + \alpha_{1,i}\frac{\Delta REV_{i,t}}{A_{i,t-1}} + \alpha_{2,i}\frac{PPE_{i,t}}{A_{i,t-1}} + \alpha_{3,i}\frac{ROA_{i,t}}{A_{i,t-1}} + \varepsilon_{i,t}, \tag{13}$$

$$NA\_PMJ_{i,t} = \hat{\alpha}_{0,i}\left(\frac{1}{A_{i,t-1}}\right) + \hat{\alpha}_{1,i}\frac{\Delta REV_{i,t}-\Delta REC_{i,t}}{A_{i,t-1}} + \hat{\alpha}_{2,i}\frac{PPE_{i,t}}{A_{i,t-1}} + \hat{\alpha}_{3,i}\frac{ROA_{i,t}}{A_{i,t-1}}, \tag{14}$$

$$AA\_PMJ_{i,t\_} = \frac{TA_{i,t}}{A_{i,t-1}} - NA\_PMJ_{i,t}, \tag{15}$$

Where *ROA* is the earnings before extraordinary items and discontinued operations in year *t* for firm *i*.

Appendix B: Variables Definitions

Dependent variables (Suppliers)	
AA_J	Jones 1991 abnormal accruals. *AA_J* is the difference between firm-level total accruals and fitted normal accruals at industry-year level.
AA_MJ	Modified Jones 1991 abnormal accruals (Dechow, et al. 1995). The *AA_MJ* is the difference between firm-level total accruals and fitted normal accruals at the industry-year level with adjustment of changes in accounts receivable in the regression for normal accruals.
AA_PMJ	Abnormal accruals controlling for ROA (Kothari et al. 2005), a.k.a. performance-based modified Jones model) is the difference between firm-level total accruals and fitted normal accruals at the industry-year level with ROA in the regression for normal accruals.
Variables-of-interest (Customers)	
C_AA_J	Customers' Jones abnormal accruals
C_AA_MJ	Customers' Modified Jones 1991 abnormal accruals
C_AA_PMJ	Customers' abnormal accruals controlling for ROA (Kothari et al. 2005))
Firm characteristics (Customers vs. Suppliers)	
C_MV	Market value of a customer
S_MV	Market value of a supplier
C_MV/S_MV	Market value of a customer divided by market value of a supplier
C_AT	Total assets of a customer
S_AT	Total assets of a supplier
C_AT/S_AT	Total assets of a customer divided by total assets of a supplier
Customers' firm characteristics	
C_DELTA_INV	Change in inventory from year t-1 to year t scaled by assets in year t-1
C_SALEGR	Change in sales from year t-1 to t scaled by sales in year t-1
C_DELTA_AP	Change in accounts payable from year t-1 to year t scaled by assets in year t-1
C_R&D	Customer firm R & D expense scaled by total assets at t
Suppliers' firm characteristics	
LOG_AT	Natural logarithm of total assets (AT)
LOG_AGEYR	Natural logarithm of number of years since IPO
SALEGR	Change in sales from year t-1 to t scaled by sales in year t-1
BIG	An indicator variable set to one if the auditor is a Big N auditor, and zero otherwise

CFO	Operating cash flow from continuing operation scaled by lagged total assets
R&D	R&D expense scaled by total assets at t
LEV	Debt in current liability plus long-term debt scaled by assets
B2M	Book value of equity divided by market value of equity
ISSUE_DEBT	Future increase in debt capital (current liability plus long-term debt in year t+1 scaled by assets. Set to zero if missing or negative. (see Carter et al. 2007, and Dou et al. 2016)
ISSUE_EQ	Future increase in equity capital (book equity) in year t+1 scaled by assets. Set to zero if missing or negative. (see Carter et al. 2007, and Dou et al. 2016)
Other incentive variables (Suppliers)	
AMP RATIO	Coefficient of variation of production divided by coefficient of variation of demand, where production (O_{it}) with the difference between change in inventory from year t to year t+1 and COGS, and demand (D_t) is measured with COGS

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TABLE 1

Sample selection and summary statistics

The sample of abnormal accruals has 3,485 unique supplier firms and 1,220 unique customer firms. The sample period spans from 1987 to 2015. Variable definitions are provided in Appendix B. If a firm has multiple customers, we keep the customer with the largest sales with the supplier. Panel A shows the procedure of sample selection. Panel B reports summary statistics for both customers and suppliers. Panel C and D show the industry distribution for customers and suppliers, respectively.

Panel A: Sample selection

Sample selection	No. of observations	
Customer and supplier matching file originated from Compustat segment files from 1987 to 2015	74,482	
less: Obs. missing customers' sales information	(12,078)	
Subtotal: major customer segment file		62,404
less: customers that are not the largest customer of a supplier	(37,853)	
Subtotal: The sample consisting of customers with the largest share of sales of their suppliers		24,551
less: financial supplier firms	(326)	
less: Obs. with missing SIC information for either suppliers or customers	(8,242)	
less: firm with age year less than zero	(47)	
less: records with the same customer key and supplier key	(100)	
The final sample		15,252

Panel B: Summary statistics for customers and suppliers

Variable	N	Mean	Std Dev	Median	Q1	Q3	Min	Max
Size measures (Customers and suppliers)								
C_MV	15,252	56,834	80,082	20,658	4,447	70,854	0	626,550
S_MV	15,252	2,582	13,147	151	31	798	0	321,147
C_MV / S_MV	15,251	3,419	101,739	105	16	597	0	8,488,943
C_AT	15,252	58,132	94,956	22,572	5,479	74,708	0	805,666
S_AT	15,252	1,899	9,822	144	37	756	0	387,692
C_AT / S_AT	15,252	1,158	10,025	105	19	523	0	998,630
Accruals measures (Customers)								
C_AA_J	15,252	-0.012	0.065	-0.006	-0.038	0.020	-0.282	0.159
C_AA_MJ	15,252	-0.012	0.065	-0.006	-0.038	0.021	-0.275	0.168
C_AA_PMJ	15,252	-0.020	0.059	-0.014	-0.046	0.011	-0.242	0.152
Dependent variables (Suppliers)								
S_AA_J	15,252	-0.017	0.130	-0.008	-0.065	0.045	-0.532	0.341
S_AA_MJ	15,252	-0.017	0.132	-0.008	-0.066	0.045	-0.533	0.352
S_AA_PMJ	15,252	-0.017	0.122	-0.015	-0.067	0.038	-1.400	1.167
Firm characteristics (Customers)								
C_R&D	15,252	0.032	0.044	0.007	0.000	0.054	0.000	0.191
C_DELTA_INV	15,252	0.016	0.058	0.005	-0.002	0.022	-0.397	2.916
C_SALEGR	15,235	0.112	0.264	0.081	0.009	0.167	-0.920	7.479
C_DELTA_AP	15,252	0.015	0.052	0.007	-0.002	0.023	-0.741	1.917
Firm characteristics (Suppliers)								
LOG_AT	15,252	5.158	2.128	4.972	3.610	6.629	0.743	10.311
LOG_AGEYR	15,252	2.037	0.852	2.197	1.386	2.708	0.000	4.174
SALEGR	15,252	0.154	0.420	0.080	-0.048	0.250	-0.614	2.439
BIG	15,252	0.792	0.406	1.000	1.000	1.000	0.000	1.000
CFO	15,252	0.052	0.179	0.076	-0.005	0.145	-1.531	0.552
R&D	15,252	0.067	0.154	0.019	0.000	0.095	-0.037	11.427
LEV	15,252	0.196	0.193	0.154	0.012	0.320	0.000	0.782
B2M	15,252	2.780	3.569	1.842	1.073	3.213	-5.035	23.261
Other incentive variables (Suppliers)								
ISSUE_DEBT	15,252	0.033	0.077	0.000	0.000	0.027	0.000	0.454
ISSUE_EQ	15,252	0.185	0.631	0.001	0.000	0.076	0.000	4.653

Panel C: Industry breakdown of customers

1-digit SIC	Industry definition	*N*	%
0	Agriculture	1	0.01%
1	Mining, oil and construction	315	2.07%
2	Food, beverage and chemicals	2564	16.81%
3	Plastics, computer and machinery	5,616	36.82%
4	Transportation	993	6.51%
5	Wholesale and retail	4754	31.17%
6	Finance, insurance, real estate	70	0.46%
7	Arts, recreations, technical services	668	4.38%
8	Healthcare, professional and education services	85	0.56%
9	Public administration services	186	1.22%
	Total	15,252	100%

Panel D: Industry breakdown of suppliers

1-digit SIC	Industry definition	*N*	%
0	Agriculture	10	0.07%
1	Mining, oil and const.	1129	7.40%
2	Food, beverage and chemicals	3101	20.33%
3	Plastics, computer and machinery	7,907	51.84%
4	Transportation	463	3.04%
5	Wholesale and retail	658	4.31%
7	Arts, recreations, technical services	1666	10.92%
8	Healthcare, professional and education services	310	2.03%
9	Public administration services	8	0.05%
	Total	15,252	100%

TABLE 2

Regressions of suppliers' accruals variables on customers' accruals variables

This table shows regression results of suppliers' accruals on customer's accruals, based on the Jones (1991) model in Model 1, modified Jones model in Model 2 and performance-based modified Jones model in Model 3. Heteroskedasticity-robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Variable definitions are provided in Appendix B.

	Independent variables		
	JONES (_J)	*MODIFIED JONES (_MJ)*	*PERFORMANCE-BASED MODIFIED JONES (_PMJ)*
Dependent variables	*S_AA_J*	*S_AA_MJ*	*S_AA_PMJ*
	(1)	(2)	(3)
C_AA	0.048***	0.053***	0.051***
	(0.018)	(0.019)	(0.019)
C_R&D	-0.021	-0.028	-0.001
	(0.036)	(0.036)	(0.032)
LOG_AT	0.002	0.002*	0.005***
	(0.001)	(0.001)	(0.001)
LOG_AGEYR	0.014***	0.014***	0.012***
	(0.002)	(0.002)	(0.002)
SALEGR	0.003	0.016***	0.018***
	(0.004)	(0.004)	(0.004)
BIG	-0.013***	-0.013***	-0.007**
	(0.004)	(0.004)	(0.004)
CFO	-0.195***	-0.197***	-0.358***
	(0.018)	(0.018)	(0.017)
R&D	-0.187***	-0.189***	-0.171***
	(0.069)	(0.070)	(0.061)
LEV	-0.099***	-0.102***	-0.068***
	(0.009)	(0.009)	(0.008)
B2M	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)
ISSUE_DEBT	-0.056***	-0.059***	-0.036**
	(0.017)	(0.017)	(0.016)
ISSUE_EQ	-0.037***	-0.038***	-0.032***
	(0.003)	(0.003)	(0.003)
CONSTANT	0.013	0.029	0.035
	(0.040)	(0.031)	(0.032)
YEAR FE	YES	YES	YES
INDUSTRY FE	YES	YES	YES
N	15252	15252	15252
adj. R-sq	0.130	0.133	0.233

TABLE 3

Two-stage regressions of suppliers' abnormal accruals variables on customers' abnormal accruals variables

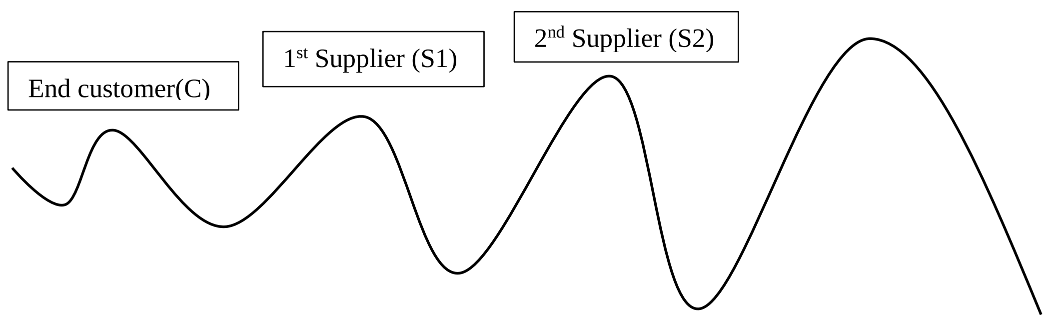
This table shows the regression results of suppliers' abnormal accruals on customers' abnormal accruals, based on the Jones (1991) model in Model (1 and 2), modified Jones model in Model (3 and 4) and performance-based modified Jones model in Model (5 and 6). Variables used in the first stage of regressions include a customer's change in inventory (*C_DELTA_INV*), its change in accounts payable (*C_DELTA_AP*), and its sales growth (*C_SALEGR*). Standard errors for customers' abnormal accruals are adjusted to take into account of estimated regressor from the first stage. Heteroskedasticity-robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Variable definitions are provided in Appendix B.

Independent variables	*JONES (_J)*		*MODIFIED JONES (_MJ)*		*PERFORMANCE-BASED MODIFIED JONES (_PMJ)*	
	C_AA_J	*S_AA_J*	*C_AA_MJ*	*S_AA_MJ*	*C_AA_PMJ*	*S_AA_PMJ*
	(1) 1st stage	(2) 2nd stage	(3) 1st stage	(4) 2nd stage	(5) 1st stage	(6) 2nd stage
C_DELTA_INV	0.461***		0.465***		0.451***	
	(0.011)		(0.011)		(0.010)	
C_SALEGR	-0.034***		-0.027***		-0.023***	
	(0.002)		(0.002)		(0.002)	
C_DELTA_AP	-0.427***		-0.402***		-0.361***	
	(0.013)		(0.013)		(0.012)	
C_R&D	-0.257***	-0.005	-0.257***	-0.009	-0.246***	0.015
	(0.011)	(0.038)	(0.011)	(0.039)	(0.010)	(0.035)
C_AA_^HAT		0.093***		0.108***		0.125**
		(0.025)		(0.026)		(0.055)
LOG_AT		0.002		0.002*		0.005***
		(0.001)		(0.001)		(0.001)
LOG_AGEYR		0.015***		0.014***		0.012***
		(0.002)		(0.002)		(0.002)
SALEGR		0.003		0.017***		0.018***
		(0.004)		(0.004)		(0.004)
BIG		-0.013***		-0.013***		-0.007**
		(0.004)		(0.004)		(0.004)
CFO		-0.195***		-0.197***		-0.358***
		(0.018)		(0.018)		(0.017)
R&D		-0.186***		-0.189***		-0.171***
		(0.069)		(0.070)		(0.061)
LEV		-0.099***		-0.102***		-0.068***
		(0.009)		(0.009)		(0.008)
B2M		0.000		0.001		0.001
		(0.001)		(0.001)		(0.001)
ISSUE_DEBT		-0.057***		-0.059***		-0.037**
		(0.017)		(0.017)		(0.016)
ISSUE_EQ		-0.037***		-0.038***		-0.032***
		(0.003)		(0.003)		(0.003)
CONSTANT	-0.001	0.016	-0.001**	0.032	-0.011***	0.038
	(0.001)	(0.040)	(0.001)	(0.030)	(0.001)	(0.032)
YEAR FE		YES		YES		YES
INDUSTRY FE		YES		YES		YES
N	15,235	15,235	15,235	15,235	15,235	15,235
adj. R-sq	0.149	0.130	0.140	0.133	0.152	0.232

TABLE 4

Bullwhip effect illustrated by magnified standard errors of abnormal accruals along the supply chain for the sample of trio firms

A three-party supply-chain sample is formed to examine the bullwhip effect in the context of abnormal accruals. Starting from an end customer C, a first supplier in relation to the end customer is identified as S1. The supplier of the first supplier is identified as S2. S1 essentially is the customer of S2 and the supplier of an end customer C. This sample corresponds to 1,212 unique pairs of Customer – 1st supplier - 2nd supplier from 1987 to 2015. Variable definitions are provided in Appendix B. If a firm has multiple customers, we keep the customer with the largest sales with the supplier (e.g., C is the largest customer of S1 and S1 is the largest customer of S2).



Variable	N	Mean	Median	Q1	Q3	Min	Max	Std Dev	F value for the test on equality of Standard Deviation for C vs. S1	F value for the test on equality of Standard Deviation for S1 vs.S2
C_AA_J	1,879	-0.025	-0.012	-0.047	0.013	-0.274	0.129	0.069		
S1_AA_J	1,879	-0.023	-0.016	-0.054	0.021	-0.441	0.166	0.084	3.74***	
S2_AA_J	1,879	-0.025	-0.018	-0.072	0.040	-0.532	0.325	0.132		2.49***
C_AA_MJ	1,879	-0.023	-0.012	-0.047	0.013	-0.266	0.135	0.067		
S1_AA_MJ	1,879	-0.022	-0.015	-0.054	0.021	-0.441	0.182	0.085	4.03***	
S2_AA_MJ	1,879	-0.024	-0.018	-0.074	0.041	-0.533	0.352	0.134		2.49***
C_AA_PMJ	1,879	-0.033	-0.025	-0.059	0.003	-0.242	0.125	0.062		
S1_AA_PMJ	1,879	-0.032	-0.028	-0.066	0.010	-0.327	0.163	0.072	3.35***	
S2_AA_PMJ	1,879	-0.021	-0.020	-0.071	0.036	-0.435	0.304	0.114		2.48***

TABLE 5

Panel A: Descriptive statistics for Amplification ratio (*AMP RATIO*)

Variable	N	Mean	Std Dev	Median	Q1	Q3	Min	Max
AMP RATIO)	12,577	1.17	0.72	1.00	0.86	1.22	0.22	5.49

Panel B: Tests on the relationship between suppliers' abnormal accruals and customers' abnormal accruals when bullwhip effect is present

Amplification ratio (*AMP RATIO*) is computed as the coefficient of variation of production over the coefficient of variation of demand. The coefficient of variation of production is measured as the standard deviation of production over three years starting from year t divided by the mean of three-year production. The coefficient of variation of demand is measured as the standard deviation of cost of goods sold over three years starting from year t divided by the mean of three-year cost of goods sold. Following Bray and Mendelson (2012), we use cost of goods sold (COGS) to proxy for demand and production derived from the inventory equation (i.e., change in inventory plus COGS) to proxy for orders. We convert COGS from FIFO method to LIFO method by subtracting the change in LIFO reserve from COGS to keep consistency. We also adjust inventory with LIFO reserve for production calculation. Each firm's demand and orders are scaled by total assets, and demand variability is normalized to one to express demand variability as percentage of demand variability. Following prior research, we consider bullwhip effects exist when *AMP RATIO*>1. We present results in two columns for each specification: below median value of *AMP RATIO* and above median value of *AMP RATIO* and report the results on tests for coefficient on *C_AA* (*C_MJ, C_PMJ*) when *AMP RATIO*<1 equal to coefficient on *C_AA* (*C_MJ, C_PMJ*) when *AMP RATIO*>1 at the bottom of the table. Variables are winzorized at the top and bottom 1%.

Independent variable	Dependent variable: *S_AA*					
	Jones		Modified Jones		Performance-based modified Jones	
	(1)	(2)	(3)	(4)	(5)	(6)
	AMP RATIO		*AMP RATIO*		*AMP RATIO*	
	< 1	*> 1*	*< 1*	*> 1*	*< 1*	*> 1*
C_AA	0.003	0.066***	-0.001	0.074***	-0.011	0.071***
	(0.026)	(0.020)	(0.026)	(0.020)	(0.024)	(0.020)
C_RD	-0.033	0.001	-0.041	-0.003	-0.003	0.001
	(0.039)	(0.031)	(0.039)	(0.031)	(0.031)	(0.028)
LOG_AT	0.002*	0.001	0.002**	0.001	0.005***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
LOG_AGEYR	0.031***	0.011***	0.031***	0.011***	0.024***	0.008***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
SALEGR	0.011**	0.001	0.029***	0.014***	0.033***	0.012***
	(0.005)	(0.003)	(0.005)	(0.003)	(0.004)	(0.003)
BIG	-0.015***	-0.010**	-0.015***	-0.010***	-0.007**	-0.006*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
CFO	-0.270***	-0.169***	-0.277***	-0.171***	-0.430***	-0.340***
	(0.011)	(0.008)	(0.011)	(0.008)	(0.009)	(0.008)

RD	-0.307***	-0.153***	-0.313***	-0.155***	-0.269***	-0.142***
	(0.016)	(0.008)	(0.017)	(0.008)	(0.013)	(0.008)
LEV	-0.118***	-0.089***	-0.120***	-0.094***	-0.079***	-0.068***
	(0.009)	(0.008)	(0.009)	(0.008)	(0.007)	(0.007)
B2M	0.001**	0.000	0.001**	0.000	0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ISSUE_DEBT	-0.010	-0.062***	-0.014	-0.062***	-0.002	-0.037**
	(0.022)	(0.017)	(0.023)	(0.018)	(0.018)	(0.016)
ISSUE_EQ	-0.035***	-0.040***	-0.037***	-0.041***	-0.025***	-0.036***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
CONSTANT	1.863***	-0.746	1.867***	-0.657	1.621***	-1.246
	(0.632)	(1.006)	(0.641)	(1.022)	(0.514)	(0.926)
YEAR FE	YES	YES	YES	YES	YES	YES
INDUSTRY FE	YES	YES	YES	YES	YES	YES
N	5,578	8,516	5,578	8,516	5,578	8,516
adj. R-sq	0.169	0.128	0.175	0.131	0.311	0.220
Tests: coefficient on *C_AA* (*C_MJ*, *C_PMJ*) when *AMP RATIO*<1 = coefficient on *C_AA* (*C_MJ*, *C_PMJ*) when *AMP RATIO*>1						
Prob > chi2	0.091*		0.050*		0.026**	

TABLE 6

Regressions of suppliers' abnormal accruals variables on customers' abnormal accruals variables with interaction term between customer's analyst forecast error and customers' abnormal accruals

This table shows the regression results of suppliers' abnormal accruals on customers' abnormal accruals interacted with analyst forecast accuracy, based on the Jones (1991) model in Model (1 and 4), modified Jones model in Model (2 and 5) and performance-based modified Jones model in Model (3 and 6). We measure customer's analyst forecast error (*AYST_ERR*) as the absolute value of the difference between mean or median EPS forecast consensus for a customer and actual EPS of a customer scaled by the customer's stock price at the end of fiscal year. *INCR_ALST_ERR* is the interaction term between customers' analyst forecast error (*ALST_ERR*) and customers' abnormal accruals. Heteroskedasticity-robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Variable definitions are provided in Appendix B.

Independent variables	Mean forecast error			Median forecast error		
	S_AA_J	*S_AA_MJ*	*S_AA_PMJ*	*S_AA_J*	*S_AA_MJ*	*S_AA_PMJ*
	[1]	[2]	[3]	[4]	[5]	[6]
C_AA_J(MJ,PMJ)	0.044**	0.050**	0.041*	0.044**	0.050**	0.041*
	(0.021)	(0.022)	(0.023)	(0.021)	(0.022)	(0.023)
INCR_AYST_ERR	0.022***	0.021***	0.033***	0.022***	0.021***	0.033***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
AYST_ERR	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
C_R&D	0.036	0.032	0.047	0.036	0.032	0.047
	(0.036)	(0.036)	(0.033)	(0.036)	(0.036)	(0.033)
LOG_AT	0.000	0.000	0.003***	0.000	0.000	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
LOG_AGEYR	0.016***	0.015***	0.013***	0.016***	0.015***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
SALEGR	0.002	0.016***	0.014***	0.002	0.016***	0.014***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
BIG	-0.008*	-0.008*	-0.004	-0.008*	-0.008*	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
CFO	-0.208***	-0.211***	-0.376***	-0.208***	-0.211***	-0.376***
	(0.016)	(0.016)	(0.015)	(0.016)	(0.016)	(0.015)
R&D	-0.318***	-0.322***	-0.296***	-0.318***	-0.322***	-0.296***
	(0.022)	(0.022)	(0.023)	(0.022)	(0.022)	(0.023)
LEV	-0.110***	-0.114***	-0.079***	-0.110***	-0.114***	-0.079***
	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.008)
B2M	0.001*	0.001**	0.001**	0.001*	0.001**	0.001**
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
ISSUE_DEBT	-0.062***	-0.063***	-0.048**	-0.062***	-0.063***	-0.048**
	(0.020)	(0.020)	(0.019)	(0.020)	(0.020)	(0.019)
ISSUE_EQ	-0.033***	-0.034***	-0.030***	-0.033***	-0.034***	-0.030***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
CONSTANT	0.018	0.035	0.043	0.018	0.035	0.043
	(0.045)	(0.035)	(0.036)	(0.045)	(0.035)	(0.036)
YEAR FE	YES	YES	YES	YES	YES	YES
INDUSTRY FE	YES	YES	YES	YES	YES	YES
N	11708	11708	11708	11708	11708	11708
adj. R-sq	0.149	0.153	0.251	0.149	0.153	0.251

TABLE 7

Regressions of suppliers' abnormal accruals variables on customers' abnormal accruals variables interacted with suppliers' auditor industry expertise

This table shows the regression results of suppliers' abnormal accruals on customers' abnormal accruals interacted with suppliers' auditor industry expertise in the customer industry, based on the Jones (1991) model in Model 1, modified Jones model in Model 2, and performance-based modified Jones model in Model 3. Following Reichelt and Wang (2010), we measure *AUD _IND_EXP* in Model 1-3 as a dummy variable equal to one if the annual market share (i.e. audit fees) of the supplier auditor is ranked in the top quintile in the customers' industry (based on 2-digit SIC codes) in a particular geographic city, and zero otherwise. *INCR_AUD_IND EXP* is the interaction term between *AUD _IND_EXP* and customers' abnormal accruals. Heteroskedasticity-robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Variable definitions are provided in Appendix B.

Independent variables	*S_AA_J*	*S_AA_MJ*	*S_AA_PMJ*
	(1)	(2)	(3)
C_AA_J(MJ,PMJ)	0.161***	0.170***	0.128**
	(0.050)	(0.051)	(0.058)
*C_AA * AUD_IND_EXP*	-0.341**	-0.370**	-0.299**
	(0.160)	(0.155)	(0.149)
AUD_IND_EXP	0.004	0.003	-0.009
	(0.010)	(0.010)	(0.011)
LOG_AT	-0.020	-0.025	-0.005
	(0.074)	(0.074)	(0.072)
C_R&D	-0.008***	-0.008***	-0.007***
	(0.003)	(0.003)	(0.002)
LOG_AGEYR	0.019***	0.019***	0.019***
	(0.004)	(0.004)	(0.004)
SALEGR	-0.016	-0.003	-0.005
	(0.012)	(0.012)	(0.015)
BIG	-0.009	-0.010	-0.002
	(0.009)	(0.009)	(0.008)
CFO	-0.107***	-0.105***	-0.250***
	(0.037)	(0.037)	(0.041)
R&D	-0.257***	-0.258***	-0.241***
	(0.041)	(0.041)	(0.054)
LEV	-0.069***	-0.071***	-0.057***
	(0.021)	(0.021)	(0.019)
B2M	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
ISSUE_DEBT	-0.042	-0.047	-0.031
	(0.046)	(0.047)	(0.054)
ISSUE_EQ	-0.039***	-0.040***	-0.039***
	(0.007)	(0.007)	(0.008)
CONSTANT	-0.002	0.002	-0.068
	(0.068)	(0.061)	(0.050)
YEAR FE	YES	YES	YES
INDUSTRY FE	YES	YES	YES
N	2,242	2,242	2,242
adj. R-sq	0.173	0.177	0.179

TABLE 8

Placebo tests using matched non-customer firms

Regressions of abnormal accruals of suppliers on abnormal accruals of non-customers vs regressions of abnormal accruals of suppliers on abnormal accruals of actual customers

Assets of customers are ranked into deciles by 2-digit SIC codes. For every customer-supplier pair, a non-customer firm in the same size decile and in the same industry as a customer is randomly selected to match this particular supplier. An artificial customer-supplier relationship is formed to substitute the real customer-supplier link to rule out the size effect. We repeat the step outlined above for the main sample used in Table 2. The procedure results in a noncustomer-supplier sample of 6,159 firm-year observations with 445 unique customers firms and 1,979 unique supplier firms. Results for this noncustomer-supplier sample are reported in Model 1-3. For comparison, we report the regression results of suppliers' abnormal accruals on customers' abnormal accruals in Model 4-6, pairing these 1,979 unique suppliers up with their actual customers from our sample in Table 2.

	SUPPLIERS				SUPPLIERS		
NON-CUSTOMERS	*S_AA_J*	*S_AA_MJ*	*S_AA_PMJ*	CUSTOMERS	*S_AA_J*	*S_AA_MJ*	*S_AA_PMJ*
	(1)	(2)	(3)		(4)	(5)	(6)
C_AA_J(MJ,PMJ)	0.035	0.030	0.043	*C_AA_J(MJ, PMJ)*	0.090***	0.099***	0.081**
	(0.037)	(0.037)	(0.039)		(0.033)	(0.034)	(0.038)
C_R&D	-0.050	-0.056	-0.046	*LOG_AT*	-0.069	-0.073	-0.042
	(0.064)	(0.064)	(0.057)		(0.050)	(0.050)	(0.045)
LOG_AT	-0.000	-0.000	0.001	*LOG_AT*	-0.000	0.000	0.002
	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
LOG_AGEYR	0.019***	0.019***	0.016***	*LOG_AGEYR*	0.018***	0.018***	0.016***
	(0.003)	(0.003)	(0.002)		(0.003)	(0.003)	(0.002)
SALEGR	0.010	0.023***	0.024***	*SALEGR*	0.010	0.023***	0.024***
	(0.007)	(0.007)	(0.007)		(0.006)	(0.007)	(0.007)
BIG	-0.009	-0.009*	-0.004	*BIG*	-0.008	-0.008	-0.004
	(0.005)	(0.005)	(0.005)		(0.005)	(0.005)	(0.005)
CFO	-0.180***	-0.180***	-0.350***	*CFO*	-0.180***	-0.179***	-0.350***
	(0.023)	(0.023)	(0.024)		(0.023)	(0.023)	(0.024)
R&D	-0.256***	-0.259***	-0.247***	*CFO*	-0.253***	-0.255***	-0.245***
	(0.029)	(0.029)	(0.032)		(0.028)	(0.029)	(0.031)
LEV	-0.087***	-0.089***	-0.063***	*LEV*	-0.089***	-0.091***	-0.064***
	(0.012)	(0.012)	(0.011)		(0.012)	(0.012)	(0.011)
B2M	0.001	0.001	0.001*	*B2M*	0.001	0.001	0.001*
	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
ISSUE_DEBT	-0.055**	-0.055*	-0.038	*ISSUE_DEBT*	-0.055**	-0.055*	-0.038
	(0.028)	(0.028)	(0.026)		(0.028)	(0.028)	(0.026)
ISSUE_EQ	-0.034***	-0.035***	-0.031***	*ISSUE_EQ*	-0.033***	-0.035***	-0.031***
	(0.005)	(0.005)	(0.006)		(0.005)	(0.005)	(0.006)
CONSTANT	0.044*	0.044	0.043	CONSTANT	0.044	0.042	0.041
	(0.027)	(0.027)	(0.032)		(0.027)	(0.028)	(0.032)
YEAR FE	YES	YES	YES	YEAR FE	YES	YES	YES
INDUSTRY FE	YES	YES	YES	INDUSTRY FE	YES	YES	YES
N	6,159	6,159	6,159	N	6,159	6,159	6,159