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The Association Fallacy – Fraud and Financial Reporting Quality in the Customer-Supplier Relationship

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1. Introduction

The behavior of a business entity is only as rational as that of its management. Without consistent discretion, entity-wide decisions may be based on one or more of a set of commonly recognized biases or fallacies. One such fallacy, the "association fallacy," refers to the phenomenon of guilt by association. Despite its recognition in the domains of law and the social sciences, the influence of the association fallacy on the behavior of business entities is not well understood.

To understand whether the association fallacy occurs between corporate entities, one may look to the model of the customer-supplier relationship. Customers and suppliers are closely economically tied and exchange more private information in their daily interactions than they do in each entity's typical relationships. There are few, if any, entity relationships with as deep a practical or economic bond. Therefore, these relationships are an excellent model for assessing the existence and strength of the association fallacy in business relationships, as the capital market scrutiny of one of the entities will likely lead to an increased scrutiny of the other. If one of those entities were publicly persecuted, it would be the fate of the "other," non-persecuted but associated entity that would reveal whether the association fallacy exists between business entities.

In this study, I focus on the behavior of customer firms with fraudulent suppliers in the periods before, during, and after the announcement of the fraud. These customer firms are not guilty of any fraudulent behavior themselves, but they are highly associated with the supplier firms by virtue of the customer-supplier relationship. Note that in demonstrating the existence of the association fallacy, the subject of interest is not the occurrence of the fraudulent supplier behavior itself, but rather the occurrence of publicized enforcement against a supplier for purported fraudulent behavior. In other words, it is the scrutiny stemming from the supposed fraud that matters, and not whether the fraud actually occurred. I regard financial reporting quality, measured inversely by earnings management behavior, as the primary lever that customer firms manipulate in reaction to the scrutiny imposed by the association fallacy. Using panel regressions of historical customer-supplier relationships, I directly measure the strength of the relationship between the announcement of supplier fraud and the degree of customer earnings management behavior. Of the three indicators of earnings management employed, only discretionary accruals demonstrated a strong model fit and statistical significance in the periods before and after an AAER. Between these two periods, the level of discretionary accruals was shown to decrease while controlling for company size, industry group, and black swan events. A subsequent cross-sectional analysis of companies larger and smaller than the median company size produced the finding that smaller customers exhibit a statistically significant decrease in discretionary accruals after a supplier AAER, whereas larger customers do not.

From the results of this study, broader conclusions may be drawn about how capital market scrutiny distorts or reinforces management incentives to present clear and accurate financial reporting. The results of the regression models are consistent with prior findings that "Abnormal current accruals has the greatest consistent explanatory power among all the proxies, perhaps because it is the component most easily subject to successful managerial manipulation" (Teoh et al., 1998, p.195). Just as discretionary accrual levels exist as the most convenient lever by which to manipulate earnings, so too is it the most convenient lever to reduce manipulation of earnings. Thus, the findings that customer discretionary accruals are more likely to decrease following a supplier AAER is consistent with the notion that customer firms act to improve their financial reporting quality and preserve their reputation. It can be concluded, then, that the disclosure of fraudulent supplier behavior does indeed correlate with decreased customer earnings management behavior, where the proxy measurements for earnings management exhibit sufficient model fit and explanatory power. To this end, the findings of this study extend beyond prior research identifying the consequences of fraud for a fraudulent firm to indicate potential positive externalities for associated, non-fraudulent firms.

The fact that smaller customer firms are more likely to adjust financial reporting quality following supplier fraud implies one of two things: that smaller customer firms are more influenced by the association fallacy than larger customer firms, or that smaller customer firms can improve their financial reporting quality to a greater degree than larger customer firms. These findings carry broader economic implications. Namely, investors should be aware of the nature of the association fallacy and its propensity to affect a company's outlook in both positive and negative ways. While increased capital market scrutiny and the resulting sentiment of guilt by association may cause reputational damage to a company, that company may also respond to the scrutiny by tightening up financial reporting practices in a way that serves to benefit both the company and its shareholders. To this end, the association fallacy may serve as an overall productive mechanism in the capital markets, as it incentivizes increased financial reporting quality for those firms that can do so.

An additional angle to consider is the role of the agency theory of overvalued equity (Jensen, 2005), which asserts that "managers of overvalued firms are likely to manage their firms' accruals upwards to prolong the overvaluation" (Kotharti et al., 2006), and the confounding effect of supplier "guilt" on this behavior. Assuming that a customer firm finds a reputational incentive to change suppliers, the desire to manage accruals upwards to achieve overvaluation and more favorable transactional outcomes enters into direct conflict with the desire to avoid scrutiny and disassociate from the fraudulent supplier firm. Absent the latter, it would be reasonably expected for evidence to exist regarding upward accrual management on the part of already-overvalued customer firms prior to going to market. Yet, while it is not easy to discern whether the customers observed to have lowered discretionary accruals were previously overvalued or undervalued, the absence of upwards accrual management across post-AAER customers indicates that, at the very least, already-overvalued customers are not *further* managing their accruals upwards.

It is important to recognize the caveats that accompany these research findings. Specifically, it should be noted that due to the limitation of available data required to complete the analysis, the sample size (N = 73) is small. Thus, it is not certain that findings generalize to the population of all Compustat firms. Further, as each customer-supplier relationship was assessed for only a consecutive three-year period, analyses incorporating additional years are indicated to increase the validity of the results and clarify the strength of the observed trends. This analysis therefore serves to suggest the existence of phenomena which may be further confirmed in future studies.

2. Background & Research Question

2.1. Prior Literature

2.1.a The Association Fallacy

Often referred to as "guilt by association," the association fallacy is a phenomenon in which one party is associated with the wrongdoing or negative image of another party without sufficient proof of affiliation. The association fallacy is a broad phenomenon with operationally equivalent synonyms across numerous fields. Psychologists refer to the interpersonal aspect of this phenomenon as “collective guilt,” and study its motivating force on individuals who have not necessarily committed wrongdoing, but who are perceived to be implicated in wrongdoing because of their connection to a wrongdoer or identification with a wrongdoing entity (Ferguson & Branscombe, 2014). In the studies of logic and law, the association fallacy is closely related to the Hasty Generalization Fallacy, a type of Inductive Fallacy in which “the sample is too small to support an inductive generalization about a population” (Willihnganz, 2008). When used in an argument or persecuting action, the association fallacy may be considered an “Argumentum ad Hominem,” in which a subject is attacked on the basis of their perceived similarity to a demonized subject. That is, “Instead of addressing the issue presented by an opponent, the ad hominem makes the opponent the issue” (Saunders, 1993).

In the context of this study, the association fallacy will not be considered as an erroneous means of direct attack or persecution. Rather, it will be understood as an underlying force between business entities, regulators, and external stakeholders that is closer in substance to collective guilt. In regard to interactions between business entities, the association fallacy refers to the perceived irresponsibility or poor ethics of a non-guilty firm that is associated with a guilty firm, by external stakeholders, regulators, and executive decision-makers. In any form, this fallacy bears heavy implications for associated non-guilty firms, who may suffer a tarnished image despite having done no wrong. Other entities with which the customer does business may opt to avoid a business relationship with the associated, non-guilty firm out of fear of unwanted affiliation. When applied to the matter of financial reporting quality, the relative strength of this underlying force takes on heavy implications for any firms whose internal control structures are not sufficiently robust, and particularly for those firms whose accounting practices could be deemed within the realm of “earnings management,” as discussed in 2.1.d. In other words, customers who experience increased scrutiny due to the publicized condemnation of a closely affiliated supplier firm may also experience more negative ramifications related to the perception of their financial reporting practices. It is within this grey area between explicitly illegal behavior and frowned-upon, but common behavior that risk exists for customers with fraudulent suppliers. Further, it is these same customers that may find incentive in improving financial reporting quality to the greatest extent possible, in order to fully disassociate from their previously affiliated supplier. Such behavior can be described as a “disassociation reflex.”

As an example of disassociation reflex on an individual scale, consider a scenario in which a there are two cars in a single lane on a highway. The car in front is driving at a speed that is far over the speed limit, and the second car is driving slightly over the limit, but not so much so that it stands a tangible risk of being pulled over. The first car passes a police patrol car, which turns on its sirens and pulls the first car over onto the side of the road. As the second car approaches the police officer and the first car, it slows down from its excessive, but not criminally excessive speed to a speed at or below the speed limit. The motivation for this second car to slow down despite not being “guilty” of materially excessive speeding is to better withstand the increased scrutiny of the police officer and onlookers of the situation as it unfolds. Thus, the second car seeks disassociation by altering the same behavior engaged in by the first car to a “criminal” degree – in this case, the manipulation of its speed. The second car’s act of speeding slightly over the limit is a “grey-area” behavior: undesirable, but not so excessive that the second car will face formal repercussions. Applying the same framework to the financial reporting of business entities, the disassociation reflex here is represented as a sudden improvement of financial reporting quality such that any “grey-area” practices are reduced.

2.1.b. Fraud & Its Consequences

The Association of Certified Fraud Examiners cites the Black's Law Dictionary definition of fraud as "any crime for gain that uses deception as its principal modus operandus…[including] any intentional or deliberate act to deprive another of property or money by guile, deception, or other unfair means." (Garner, 2004) Fraud may occur on an internal or external basis, and the methods through which it is carried out can vary widely. In cases of internal fraud (also known as occupational fraud), according to the ACFE 2020 Report to the Nations, the average fraudster is male, has no prior charges, and is aged between 31 and 45. As the nature of occupational fraud requires the misappropriation of company assets, departments involved in the management and control of said assets - operations, accounting and upper management - are the most likely sources (ACFE, 2020). According to the 2020 PwC Global Economic Crime and Fraud Survey, customer fraud (35%), cybercrime (34%), asset misappropriation (31%), bribery/corruption (30%) and accounting fraud (28%) are the most frequently occurring types of fraudulent activity. Third parties, such as vendors and suppliers, were the source of significant fraud for nearly a fifth of the respondents; yet, "half [of all respondents] lack a mature third-party risk program - and 21% have no third-party due diligence or monitoring program at all." (PwC, 2020).

Fraud is pervasive and costly, and exposes common inefficiencies present in many operating businesses. The 2020 Report to the Nations indicates that in the United States and Canada, the median loss per fraud case is approximately 120,000 USD, with the top 25% of cases rising to nearly 570,000 USD (ACFE, 2020). Per the PwC survey, (47%) of the 5000+ respondents had experienced some form of fraud in the past two years. Cumulatively, these reported frauds totaled to $42B in incurred losses (PwC, 2020). When one observes a wider range of years, estimated losses grow to incredible proportions. In fact, the total market capitalization loss across just five well-known cases of fraud publicized over the span of 2001 to 2002– Enron, Worldcom, Qwest, Global Crossing and Tyco – is estimated at approximately $460B (Cotton, 2002). At the broadest scope of analysis, a 2019 Crowe report found the global average loss rate over the period of 1997 to 2018 to be $5.1T, or 6.05% of GDP (Gee & Button, 2019). In addition to their severity, capital market consequences of fraud fall heavily upon the unassuming investing public. Often, fraud results in substantial negative price reactions that have historically sent shares tumbling by as much as 92% (Rezaee, 2005). Victims are exposed to immense volatility and forced to incur severe losses, and while some recourse may be found through IRC Section 165 in mitigating these losses, formal restitution can take many years and is of no guarantee.

The true cost of fraud extends far beyond immediately apparent monetary loss. At a systemic level, distorted information renders capital markets less efficient through misinformed overinvestments and subsequent overly cautious under-investments (Kumar & Langberg, 2009). For uninformed shareholders, the consequent reduction in stock market value and credit rating following the discovery of fraud makes it extremely difficult to recoup losses. Over time, fraud has therefore reduced the general sentiment of trust and faith in the competency of boards of directors to protect investors' shares (Zahra et al., 2005). More insidious are the societal effects of fraud, which are noted by Moore and Mills in a 1990 study to be: "(a) diminished faith in a free economy and in business leaders, (b) loss of confidence in political institutions, processes, and leaders, and (c) erosion of public morality." Such destructive trends have arisen through repeated violations of trust and failure of proper internal controls and regulatory oversight.

To assess for the existence of fraud, researchers look to the occurrence of regulatory action arising from a financial reporting violation. One indicator of reporting violations commonly used in academic research (Feroz, Park & Pastena, 1991; Bonner, Palmrose & Young, 1998; Dechow, Larson & Sloan 2011); is the occurrence of an AAER, or Accounting and Auditing Enforcement

Release. Published by the Securities and Exchange Commission, AAERs are "financial reporting related enforcement actions concerning civil lawsuits brought by the Commission in federal court and notices and orders concerning the institution and/or settlement of administrative proceedings" (SEC, 2021). Because AAERs are publicly accessible documents, and SEC enforcement against a public company is often a subject of interest to investors, observing the occurrence of an AAER publication is an appropriate method of measuring the fraudulent behavior of a firm. As mentioned previously, the very existence of the AAER is the focus of this analysis, and not the outcome of the enforcement. This distinction is important in understanding the motivations of the customer, as the behavior change or lack thereof on the customer's part must be tied to an event that would invoke additional scrutiny into all entities associated with the publicly prosecuted entity.

2.1.c. The Customer-Supplier Relationship

The actions of a customer carry consequences for a supplier, and vice-versa. As customer-supplier relationships proceed, repeated transactions increase interfirm interdependence and tie the success of each firm to that of the other, making shared trust and avoidance of opportunistic behavior critical to each firm's individual performance (Laaksonen et al., 2008). The violation of this trust and deterioration of the relationship carries costs for each firm, in no case more significantly so than in the event of fraud. The fraudulent act itself, as well as the publicization and litigation related to the act, are a substantial risk to the non-guilty customer or supplier and may provoke a change in behavior. On the supplier side, Banerjee, Dasgupta & Shi found an association between public disclosure of customer financial misconduct and both declining R&D expenses and patent creation (Banerjee et al., 2020). On the customer side, customers often react to news of a fraud firm's behavior with "reputational sanctions," damaging the fraud firm's operating performance to protect their own (Johnson et al., 2014). Whether the reactionary measures undertaken by customer firms includes measures related to earnings management is a critical consideration in this study.

2.1.d. Earnings Management for Customers

In her 1989 article *Commentary on Earnings Management*, Katherine Schipper defined earnings management as “a purposeful intervention in the external financial reporting process, with the intent of obtaining some private gain.” (p.92) The term has since become a universal euphemism for various financial reporting techniques and practices that misrepresent a company’s operating performance and outlook. In the broadest sense, earnings management tends to occur when “firm management has the opportunity to make accounting decisions that change reported income, and exploits those opportunities” (Weil, 2009). Thus, in contrast to explicitly illegal techniques that constitute financial reporting fraud, earnings management practices reside on a spectrum of legality, ranging from aggressive, but legitimate, to those that are subject to fines and cease-and-desist orders by the SEC. A recent example of the latter is the practice of “pulling in” future sales to be recognized in the present, for which companies such as Under Armour and the Marvell Technology Group have faced SEC action (Whoriskey, 2019). Based on the disassociation reflex framework described in 2.1.a, earnings management behavior that has not faced formal persecution is akin to “grey-area” behavior.

Earnings management is generally regarded as an eroding force to financial reporting quality (Healy & Wahlen, 1999). In particular, Xie noted how earnings management creates an agency problem among top management whose compensation is tied to the earnings they themselves report and diminishes the ability of the public to make informed investments (Xie, 2001). Other studies (Teoh, Welch and Wong, 1998a; Shivakumar, 1999) have observed manager inflation of earnings to achieve a more favorable perception from investors prior to seasoned equity offerings, ultimately leading to poorer stock market performance. Further, earnings management behavior has been shown to be suggestive of both current and future fraudulent behavior (Perols & Lougee, 2011). In an aggregate sense, earnings management lowers earnings quality, and by extension, financial reporting quality (Bissessur, p.39). Therefore, the presence and frequency of earnings management behavior is a strong proxy measure for financial reporting quality. Discretionary accruals (Dechow, Ge and Scharand, p.171) and meeting-or-beating forecasts (Dechow, Ge and Schrand, p.14-15) are two commonly used measures for detection of earnings management.

Other studies demonstrate that firms with higher financial reporting quality experience higher investment efficiency - that is, lower rates of over-investment and under-investment - and higher resilience to macro-economic fluctuations (Verdi, 2006; Biddle et al., 2009). Thus, an incentive exists for customer firms to maintain high financial reporting transparency following supplier fraud, both to prevent increased scrutiny from investors and regulators and to expedite the process of changing suppliers, who may assess the current and future performance of the customer as part of the deal formation process.

2.2. Hypothesis Development

Given that incentives exist for customers to improve financial reporting quality in response to increased scrutiny, it is feasible that one would observe a pattern of behavior change in a customer over the time periods in which a scrutiny-inducing event unfolds. The interdependent nature of the customer-supplier relationship suggests that the conditions experienced by one of the two entities is also strongly felt by the other. Therefore, the public condemnation of a supplier for fraudulent behavior presents a context in which one would expect the increased level of scrutiny to coincide with a change in customer behavior - specifically, an increase in financial reporting quality via a decrease in earnings management behavior. It is reasonable that customer firms would feel more inclined to reduce earnings management behavior to protect its reputation and disassociate from the supplier firm. This translates to either a reduction in the degree of existing earnings management behavior, or at the least the continuation of an avoidance of earnings management behavior, in the year during and after the condemnation of the supplier.

A contrasting perspective is that (given the assumption that the customer firm is innocent) a customer firm would not consider modification to its own financial reporting practices to be necessary to withstand capital market scrutiny. Alternatively, a customer firm that engages in earnings management behavior may find concern in dramatically reducing such behavior following a supplier AAER. To articulate this point, consider again the example of a police car that has pulled over a speeding car on the side of the highway. If another approaching driver slammed hard on their brakes upon seeing the lights of the police car, the police officer may perceive this as an indicator that this driver, too, was speeding excessively over the limit. So, too, may a customer firm seek to avoid “slamming the brakes” on certain accounting practices to avoid unintentionally invoking even more intense scrutiny than what it already must sustain.

The primary research questions to be addressed are: Does financial misconduct detection affect the financial reporting quality of the fraudulent firm’s major customers? If so, are changes in financial reporting quality of a fraudulent firm’s major customers (as measured by level of earnings management) related to the size of the customers? The resulting hypotheses are as follows (in alternative form):

H1: Customer firms' earnings management behavior decreases after the detection of a supplier firms' frauds.

H2: The improvement in customer firms' financial reporting quality is positively associated with size.

3. Research Design & Data

3.1 Research Design

The overall design of the research process is represented by the following equation:

$$(1 \div FRQ_{i,t}) \propto EM_{i,t} = f(AAER\_AFTER_{i,t}, SIZE, ROA, BTM, LEV)$$

This equation states that for a given time series, the inverse of financial reporting quality is equal to the level of earnings management behavior, which is equal to the level of customer earnings management behavior relative to the occurrence of the supplier fraud.

The independent variable *AAER_AFTER* in this analysis is an indicator variable that takes the value of one if the observation is from a year after the publication of an SEC Accounting and Auditing Enforcement Release (AAER) for a given supplier firm, and zero otherwise. The dependent variable is the corresponding customer firm's earnings management behavior. The occurrence of change in financial reporting quality uses earnings management behavior as an inverse measure; that is, a reduction of earnings management from the previous year indicates improved financial reporting quality, while an increase or new occurrence of earnings management as compared to the previous year indicates worsening financial reporting quality. I measure earnings management behavior with three variables: discretionary accruals (*DISCACCR*), meeting-or-just-beating Earnings per Share estimates (*MJBEPS*), and meeting-or-just-beating previous Net Income (*MJBNI*). Because multiple observations are observed repeatedly over time, a panel regression that controls for company size and size was indicated. To control for variety in company size, all financial data used in the calculation of discretionary accruals was scaled by Total Assets. To control for industry, the regression model used to determine "expected accruals" was grouped by SIC code. Moreover, a date range of 45 years (1971 to 2015, inclusive) controls for the confounding effect of any black swan events that may atypically motivate earnings management behavior changes in any one year.

3.2 Data Preparation & Analysis

Data from the study *Detecting Accounting Fraud in Publicly Traded U.S. Firms Using a Machine Learning Approach* containing AAER announcements from 1971 to 2015 was retrieved from an open-source repository (Bao et al., 2020). Using Compustat, CIK numbers were matched to the names of 738 unique suppliers. Additional identifying information was collected for each supplier, including ticker symbol, CUSIP, and legal name. Supplier CUSIP numbers were then used to retrieve all available matching customers from the Compustat Customer Segments database, producing 5,171 customer-supplier instances over 45 years. The resulting customer names required extensive manual cleaning to remove separate names for the same entity (i.e. General Motors, Inc. and GEN MTR), and also to remove entities that were either too broad or not appropriate for use in the study (i.e. "South America," "NOT REPORTED"). Accordingly, customer-supplier relationships with government entities were removed during this process. After cleaning, 202 unique customer names remained.

Usable customer names were then manually matched to their GVKEYs, and the GVKEYs were used to collect relevant financial data in the years before, during, and after the corresponding supplier's AAER announcement. For example, one Customer-Supplier relationship studied was General Electric and LaBarge, Inc., in which General Electric was a Customer and LaBarge, Inc. was a supplier. LaBarge, Inc. was named in an AAER in 2006, so relevant information for General Electric was collected for the years 2004, 2005, and 2006. Retrieved data included Estimate and Actual EPS, Total Assets, EBIT, Net Income, Book Value per Share, Net Operating Cash Flow, PP&E, Accounts Receivable Increase/Decrease, and Total Revenues.

Discretionary accruals were calculated using the Modified Jones Model, as shown below:

$$\frac{ACCR_{\mathrm{t}}}{A_{\mathrm{t}-1}} = \frac{(NI\ -\ CFOP)_{\mathrm{t}}}{A_{\mathrm{t}-1}} = \frac{\alpha_1}{A_{\mathrm{t}-1}} + \alpha_2\,\frac{(\Delta REV_{\mathrm{t}}\ - \Delta AR_{\mathrm{t}})}{A_{\mathrm{t}-1}} + \alpha_3\,\frac{(PPE_{\mathrm{t}})}{A_{\mathrm{t}-1}} +\ \varepsilon_{\mathrm{t}}$$

Where, for a given year:

$ACCR_{\mathrm{t}}$ = Accruals in year *t*,

A_{t-1} = Total assets in year *t* - 1,

NI = Net Income,

CFOP = Total Funds From Operations (Cash Flow),

ΔREV_{t} = Change in Revenues between year *t* and year *t* - 1,

ΔAR_{t} = Change in Accounts Receivable between year *t* and year *t* - 1,

PPE_{t} = Gross Property, Plant & Equipment in year *t*,

$\alpha_1, \alpha_2, \alpha_3$ = Parameters to be estimated via Ordinary Least Squares (OLS) regression,

ε_{t} = Standard Error in year *t*.

Accruals were fitted using a generalized linear regression of the entire available Compustat sample, the output of which contained 227,657 observations. Industries with less than 20 industry-year observations (where an "industry-year" refers to the concatenation of the fiscal year of the observation and the firm's 2-digit SIC code) were dropped, leaving 176,277 observations grouped by SIC code and year. Next, observations with no studentized residual output were dropped, leaving 175,612 observations remaining. To ensure robustness, these residuals were then winsorized at the 1st and 99th percentiles. These predicted values served as the "fitted accruals," and were integrated into the working customer-supplier relationship sample by matching to industry-year. The fitted accruals were then compared to the actual calculated accruals in each observation, with "discretionary accruals" calculated as the absolute value of the difference between actual accruals and fitted accruals. As extreme values were already controlled for in the regression of the entire Compustat sample, the discretionary accruals used in the reduced customer sample were not winsorized.

Meet-or-Just-Beat behavior (MJB) was analyzed in the form of two distinct variables - MJB via Earnings per Share (*MJBEPS*) and MJB via Changes in Net Income (*MJBNI*). Both *MJBEPS* and *MJBNI* were created as dummy variables, with a "0" representing the failure to satisfy a given condition (and thus the absence of MJB) and a "1" representing the satisfaction of a given condition (and thus the existence of MJB). In regard to Earnings per Share, an observation of MJB was considered to have occurred when the EPS variance - that is, the difference between the analyst estimate of EPS and the actual reported EPS - exceeded $0.05. In regard to Net Income, MJB was considered to have occurred when a firm's reported change in net income divided by BV per share was either equal to zero, or within 5% of the firm's reported net income divided by BV per share. Four control variables were also added to the sample for each observation: *SIZE*, *ROA*, *BTM*, and *LEV*. These variables are commonly used as control variables in the assessment of financial reporting quality (Dou et al., 2018; Bharath et al., 2013; Rajgopal & Venkatachalam, 2010). A value of 0 was assigned in the case that a customer did not have

ROA, *BTM* or *LEV* available for a given year. Finally, three binary columns, *AAER_BEFORE*, *AAER_DURING*, and *AAER_AFTER* were added based on the fiscal year and AAER year to complete the regression analysis more efficiently. The final sample contained 219 observations of 73 customer-supplier relationships from 1988 to 2016. Each row represents a single year of a single relationship, and each relationship is represented by three consecutive rows containing data from the years before, during and after the supplier AAER.

Once imported into SAS, descriptive summary tables and distribution analyses were used to understand the general nature of the data. For *DISCACCR*, a one-sample t-test was used to discern whether the sample customers' discretionary accruals were different from the mean of the full Compustat sample. Then, to test H1, three separate linear regression models were constructed using the aforementioned variables, which each had 73 cross sections and a time series length of 3 periods. For *DISCACCR*, a PROC PANEL One-Way Random-Effects Model using the generalized method of moments (GMM) was employed. Variance components were calculated using the Fuller and Battese method. For *MJBEPS* and *MJBNI*, a logit model was used. The relationship between *AAER_BEFORE* and *AAER_DURING*, and the relationship between *AAER_DURING* and *AAER_AFTER*, were both tested. Because *AAER_BEFORE* served as a reference group in the regression models, the relationship between *AAER_BEFORE* and *AAER_AFTER* was not directly assessed. However, by comparing *AAER_BEFORE* vs. *AAER_DURING* and *AAER_DURING* vs. *AAER_AFTER*, conclusions about *AAER_BEFORE* vs. *AAER_AFTER* may be indirectly drawn.

Finally, to assess H2, the customer-supplier sample was split into two subsamples using the SUBS dummy variable. A "0" indicates a customer with a size below the 50th percentile, and a "1" indicates a customer with a size at or above the 50th percentile. In both subsamples, a one-way random effects regression was used to test for statistical significance for discretionary accrual changes in either the year of or the year after the supplier AAER.

4. Results

4.1. Descriptive Analysis

Table 1 presents descriptive summary statistics for the discretionary accruals generated from the full Compustat sample. With a median of approximately 0.0072 and maximum of ~0.03, the residuals fall comfortably within the expected range. A high coefficient of variation is explained by the continuing presence of relatively "extreme" values; however, unlike the truly extreme values eliminated via winsorization, such "extreme" values do not carry the potential of a substantial confounding effect and are rather indications of the glaring significance of certain discretionary accruals pursued by management. They are therefore retained. As presented in Plot 1, the distribution of discretionary accruals from the full Compustat sample assumes a strong normal shape but contains two concentrated "pockets" of deviation at both ~.015 and ~.034, the latter of which resides near the maximum level of discretionary accruals. The extreme nature of this grouping near the maximum is attributable to the use of the absolute value of discretionary accruals. Had negative discretionary accruals retained their negativity in the calculation of residuals, the resulting distribution of extreme positive and extreme negative accruals would allocate extreme values on both sides of the normal distribution.

The prominence of these extreme discretionary accruals becomes more dramatic when viewed through probability plots. In both normal and lognormal analyses (Plots 2 and 3), a substantial trendline deviation was observed at the 99th percentile, as the absolute value of these discretionary accruals jumped by more than the entire range of all values up to the 99th percentile. The visible concentration of extreme values simply reflects the effect of including discretionary accruals at their absolute value; if taken at both positive and negative values, the extreme negative discretionary accruals would somewhat lessen the dramatic shape of the current probability plots. Further, while the thickness of the plot line makes the points above the 99th percentile appear to be as prominent as those in lower percentiles, this is not actually the case. There are simply so many observations that the plot line appears to retain the same boldness and thickness throughout. Given the observed distribution for all observations in all industry-years, it is logical that the customer-supplier sample would show a similar, but far less pronounced pattern. Due to the extreme difference in observations (~176k for full Compustat versus 231 for the final sample), behavior on the plotline would logically exhibit a substantially depressed version of the full Compustat pattern up to the 99th percentile, with potentially one or two "extreme" values beyond it.

A distribution analysis of the *DISCACCR* variable in the customer-supplier sample confirms this behavior to be the case with a proportionately similar histogram, and normal plot, as presented in Plots 4 and 5. As anticipated, the probability plots exhibit highly similar behavior to the larger Compustat sample - a rolling concave-down-to-concave-up shape up to the 99th percentile, and then a jump in value that exceeds the range of the 99th to the 1st percentile. With a sample size of only 231, the behavior is far less dramatically apparent than the Compustat sample, but observable nonetheless. To be able to assert this similarity more confidently, however, a t-test is indicated. Using the Compustat sample mean of 0.0075940, a one-sample t-test was conducted using a 95% confidence level where H0 = no difference between sample mean and H1 = Pr > |t| is not greater than 0.90. As presented in Table 2, the customer-supplier sample fails to reject the null hypothesis, and it may be safely assumed that there is no statistically significant difference between the distributions of discretionary accruals in the final customer-supplier sample and those in the larger Compustat sample.

In analyzing the customer-supplier sample further, it is important to consider how descriptive statistics differ between pre-AAER and post-AAER years. Table 3 presents the mean, standard deviation, and minimum and maximum values for discretionary accruals (*DISCACCR*), *MJBNI*, and *MJBEPS*. For *DISCACCR*, the mean decreases consistently over the three consecutive time periods. Further, the standard deviation decreases rather noticeably, suggesting an increased clustering around the mean. The minimum level of discretionary accruals shows the most dramatic drop over the three periods, but given that this is a single value, there is little insight to be found regarding the aggregate behavior of all customers. Because *MJBEPS* and *MJBNI* are dummy variables, their means simply represent the relative frequency of a "1" occurring. For *MJBEPS*, this probability is ~23% in *AAER_BEFORE*, ~28% in *AAER_DURING*, and ~26% in *AAER_AFTER*. For *MJBNI*, this probability is ~7% in *AAER_BEFORE*, ~1% in *AAER_DURING*, and ~15% in *AAER_AFTER*. The standard deviation for *MJBEPS* did not change meaningfully, while the standard deviation for *MJBNI* dropped dramatically in the *AAER_DURING* period and subsequently rose to previous levels in *AAER_AFTER*. While it is not possible to declare anything conclusive about the predictability of earnings management behavior using only these results, it is interesting to note that the frequency of MJB occurrence does not appear to decrease consistently with time for *MJBEPS* and *MJBNI* as was expected. In contrast, *DISCACCR* does depict a promising, steady drop between periods.

Considering results at the industry group level offers additional insights. Accordingly, shown in Table 4 are data for discretionary accrual levels by 2-digit SIC codes. Industry group 42 (Motor Freight Transportation and Warehousing) has the highest average level of discretionary accruals, while industry group 45 (Transportation by Air) has the lowest. While the number of observations for each industry group varies widely, this has no significant bearing on the accuracy of descriptive calculations, as the expected accruals for each industry were calculated using the entire Compustat sample. Rather, this simply reflects the random distribution of industries within the final sample. The highest discretionary accrual recorded is found under industry group 29 (Petroleum and coal products), while the smallest is found under industry group 48 (Communications).

4.2 Multivariate Analysis Results

4.2.1 H1

As shown in Table 5, the *DISCACCR* variable produced an extremely robust model fit and satisfactory variance and Hausman Test results. When using *AAER_BEFORE* as a reference group, there is a statistically insignificant (Pr > |t| of 0.6978) decrease in *AAER_DURING* discretionary accruals, and a statistically significant (Pr > |t| of 0.007) decrease in *AAER_AFTER* discretionary accruals. In other words, there is a statistically significant reduction in discretionary accruals in the year after an AAER announcement versus the year before, but no such case when comparing the year before to the year of the AAER announcement. All continuous predictors (*SIZE*, *ROA*, *LEV*, *BTM*) display a negative correlation with *DISCACCR*; that is, as *SIZE*, for example, increases, *DISACCR* decreases. Of these relationships, however, only that between *BTM* and *DISCACCR* is significant.

Table 6 presents results for the *MJBEPS* variable under the logit model. While the results of *MJBEPS* cannot be directly compared to those of *DISCACCR* due to the use a generalized estimating equation (GEE) approach and logit model, Pr > |Z| values indicate that

AAER_DURING and *AAER_AFTER* are not significant for this variable. Further, Chi-Square analysis indicates that neither *AAER_DURING* nor *AAER_AFTER* exhibit a particularly strong goodness of fit. Of the control variables used, *BTM* exhibits the highest goodness of fit, with *ROA* not far behind. *SIZE* and *LEV*, meanwhile, are approximately as insignificant as the target variables. The lack of significance for *MJBEPS* limits the model's potential to deliver any conclusive insights into changes in earnings management behavior.

Results for the *MJBNI* variable, as presented in Table 7, depict *AAER_DURING* vs. *AAER_AFTER* to be closely significant. Interestingly, *AAER_DURING* vs. *AAER_AFTER* was found to be significant for the wald-chisq test but insignificant for the Z-test. However, it is reassuring that the Type 3 GEE Analysis test reports *AAER_DURING* as significant, as Type 3 results are generally more trustworthy than the regular Type 1 results. Similarly to *DISCACCR* and *MJBEPS*, there is no statistical significance to the relationship between *AAER_BEFORE* and *AAER_DURING*. The QIC is notably lower for *MJBNI* than for *MJBEPS*, suggesting that the MJBNI regression has higher explanatory power than the *MJBEPS* regression. However, it cannot be asserted that the *MJBNI* variable has a better or worse model fit than that of the continuous variables *DISCACCR*. Overall, in the *AAER_DURING* period, *MJBNI* is more likely to be "0" than in *AAER_BEFORE* (reference group). In the *AAER_AFTER* period, *MJBNI* is marginally less likely to be "0" than in *AAER_DURING* but not significantly so. Therefore, it can be asserted that *MJBNI* is generally more likely to have a value of "0" in the period during and following the announcement of an AAER than in the period before. It should be noted, however, that there is a significant imbalance in this predictor variable, as there were very few "1" values to begin with. A larger sample size would potentially enhance the robustness of these results by providing additional observations with *MJBNI* present.

4.2.2 H2

Tables 8 and 9 depict cross-sectional results for the *DISCACCR* variable, using two subsamples of “small” company size and “large” company size. In the case of “small” customers, there is a statistically significant decrease in discretionary accruals in the year following a supplier AAER. All other variables are not statistically significant. For “large” customers, there are no statistically significant variables. These directly contradict H2, as they fail to demonstrate a positive association between customer size and financial reporting quality. In fact, it is the smaller customer group that demonstrates a positive association under cross-sectional analysis. One potential explanation for this is that while larger customers may receive additional scrutiny from a wider body of stakeholders, they have lower levels of earnings management and higher levels of financial reporting quality such that there is less “room to improve.” Because larger customers are already well-established, they may actually be less susceptible to guilt by association than smaller firms that have not yet established as strong of a reputation. Conversely, smaller firms may not experience similar levels of scrutiny to motivate financial reporting quality improvement prior to the supplier AAER, and so the subsequent improvement is much more notable in scale. However, it cannot be concluded that smaller firms have overall poorer earnings management practices, or that a supplier AAER leads to a decrease in earnings management, because the Hausman tests in both models fail to disprove the presence of random effects.

5. Conclusion

Discretionary accruals carry significant explanatory power in the context of customer earnings management behavior changes following a supplier AAER. In the year of and the year following the announcement of a supplier AAER, it is likely that customer firms decrease discretionary accruals from the year before the supplier AAER. More customers experience negative EPS forecast errors in the post-AAER year, and those negative EPS forecast errors have larger absolute values than in the pre-AAER year. However, this predictor has a comparatively poor model fit and thus is not an optimal proxy measurement of earnings management behavior. Meet-or-Just-Beat behavior as measured by changes in net income has a somewhat better model fit than Meet-or-Just Beat behavior as measured by Earnings per Share, but lacks explanatory power.

Further research is indicated to explain specific changes in discretionary accrual levels for firms that are facing increased scrutiny or capital market pressure. In addition, investigation into whether association fallacy-induced earnings management changes are rewarded by minimal reputational impact or a more efficient process of new supplier acquisition for customer firms would aid in clarifying whether the behavior observed in this study reflects decisions of true strategic value, or whether such behavior is simply a “knee-jerk” reaction of little positive consequence. These distinct aspects of the association fallacy - how the customer firm perceives its situation, the actions it takes in response, and how broader stakeholders perceive those actions - are not necessarily rational and are certainly not consistent. However, the findings in this study establish a strong basis for further research insofar as the association fallacy, as defined in the context of business interactions, is indeed present and observable in the modern business environment.

Understanding the ways in which non-guilty customers are compelled to act in the wake of their suppliers’ fraud is critical to understanding how such situations reverberate throughout a fraudulent firm’s professional network. Relationships define commerce, and any threat to a firm's relationships, baseless or otherwise, is likely to prompt a response that relates to how that firm represents and positions itself. Management stands to benefit from recognizing the reality that the association fallacy, however rational, is pervasive along with all other common modes of human irrationality. When such fallacies are not recognized, the level of reasoning in business relationships becomes no greater than that observed among children playing on a playground. In contrast, a cautious awareness of the association fallacy enables a responsible management team to better handle reputational threats and make the improvements necessary to deliver transparent, useful financial reporting to its stakeholders. With awareness and proactive improvement of earnings management practices, non-guilty firms may operate free of the burden of that which they did not commit themselves.

Appendix A: Variable Definition Table

Variable	Definition	Source
DISCACCR	Absolute value of discretionary accruals, scaled by total assets.	Manual calculation; residuals from Compustat
MJBEPS	Meet-or-Just-Beat Earnings per Share forecast. Dummy variable used to indicate occurrence/absence.	Manual calculation; EPS analyst and actual values from Compustat
MJBNI	Meet-or-Just-Beat Net Income. Dummy variable used to indicate occurrence/absence.	Manual calculation; Net Income data from Compustat
SIZE	Company size, calculated as the logarithm of total assets (AT)	Compustat
ROA	Return on Assets	Compustat
BTM	Book-to-Market Ratio	Compustat
LEV	Leverage, calculated as Long-term Debt divided by Book Equity	Compustat
AAER_BEFORE	Dummy variable representing the year before a supplier AAER.	Manual calculation
AAER_DURING	Dummy variable representing the year during a supplier AAER.	Manual calculation
AAER_AFTER	Dummy variable representing the year after a supplier AAER.	Manual calculation
SUBS	Dummy variable representing customers below (0) and at or above (1) the 50^{th} percentile of all customer sizes.	Manual calculation

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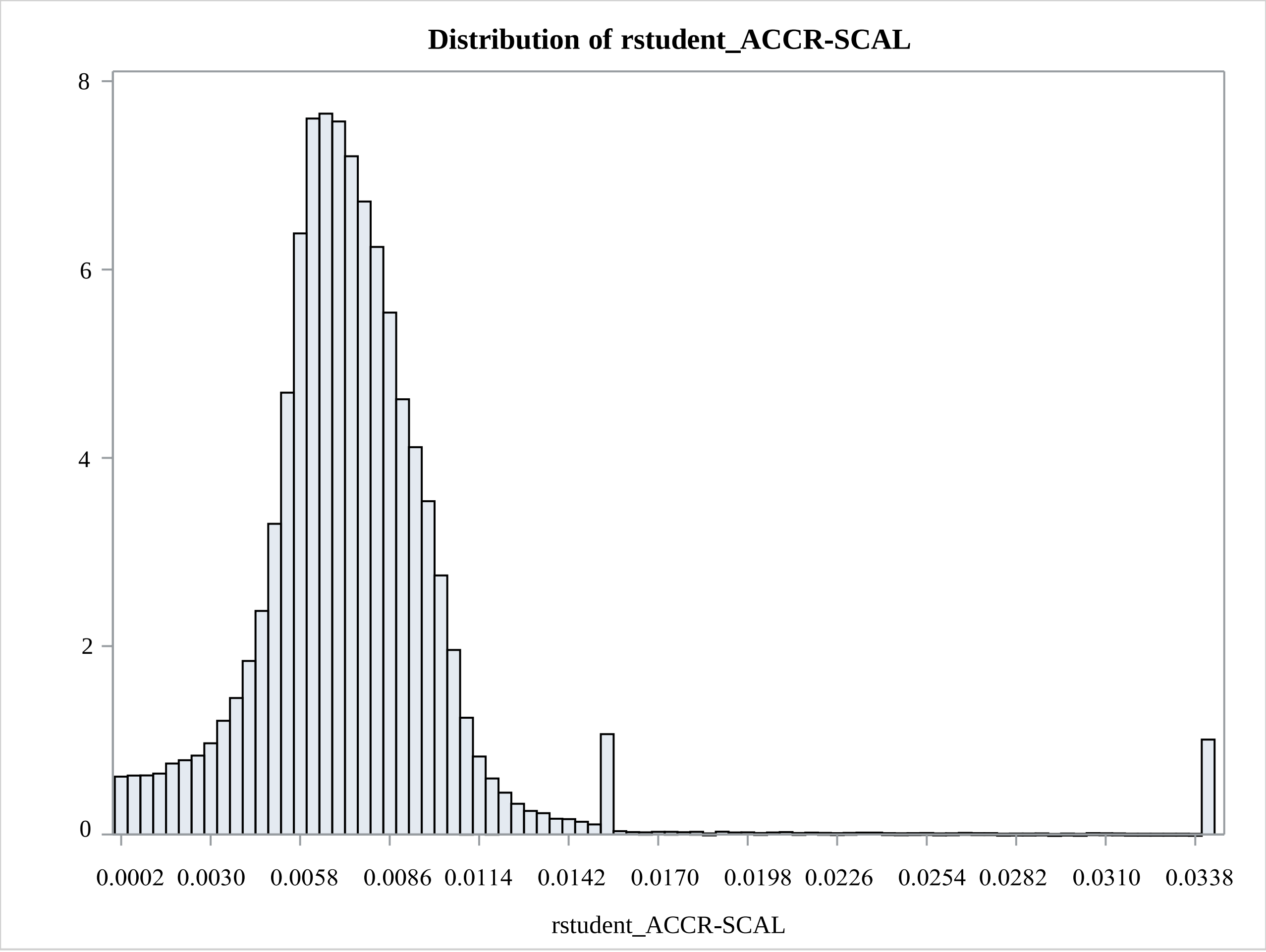
Tables and Plots

Table 1: Descriptive Summary Statistics for Full Compustat Discretionary Accruals

Analysis Variable : rstudent_ACCR-SCAL								
Mean	Std Dev	Minimum	Maximum	Lower Quartile	Median	Upper Quartile	Coeff of Variation	Corrected SS
0.0075940	0.0039297	4.4638334E-7	0.0342601	0.0058789	0.0072021	0.0087484	51.7474998	2.7118881

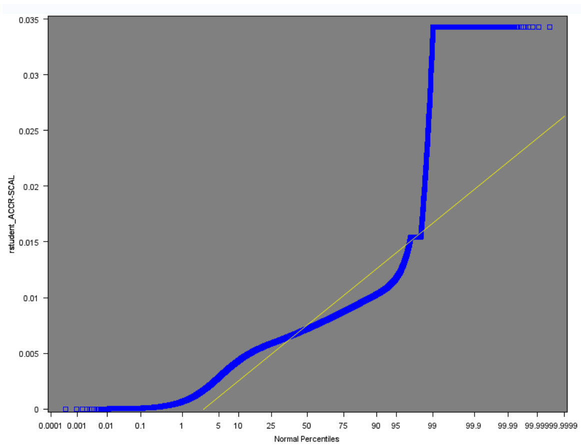
This table shows summary statistics for the discretionary accruals of the entire Compustat database sample, containing 175,612 observations."Corrected SS" represents the sum of the squared distance of data points around the mean; where Corrected SS is equal to C, V=C/N - 1.

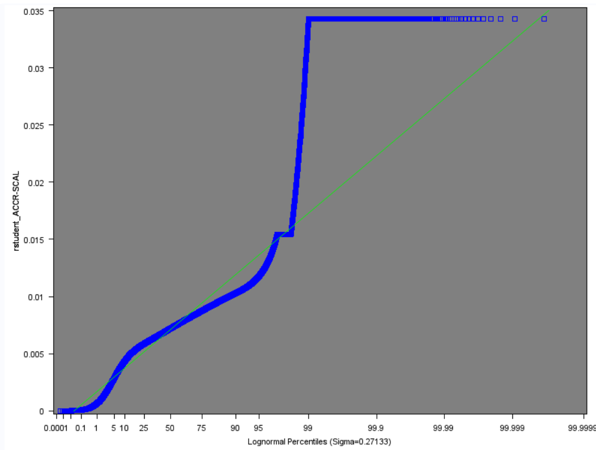
Plot 1: Normal Distribution of Full Compustat Discretionary Accruals



This plot represents the distribution of the DISCACCR variable from the entire Compustat database sample. The distribution retains an overall normal shape, with a notable concentration of extreme positive outliers.

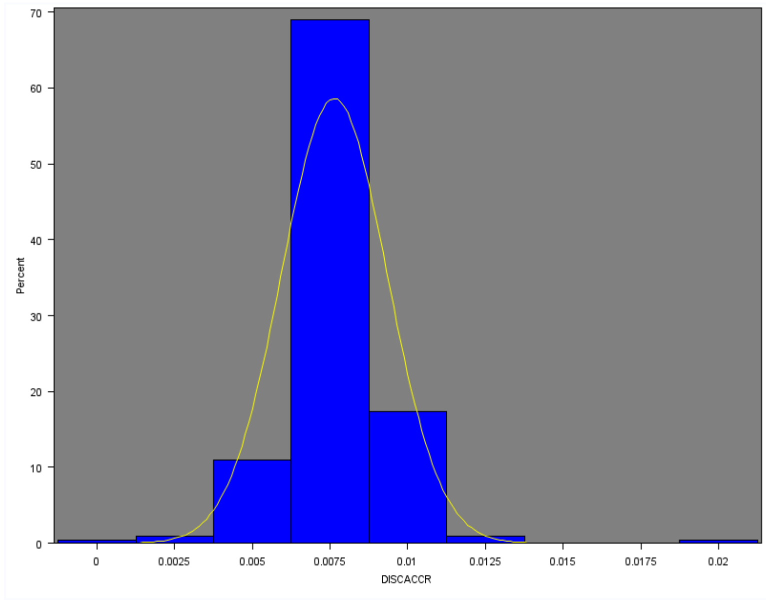
<u>Plots 2 & 3: Normal (left) and Lognormal (right) Probability Plots for Full Compustat Discretionary Accruals</u>

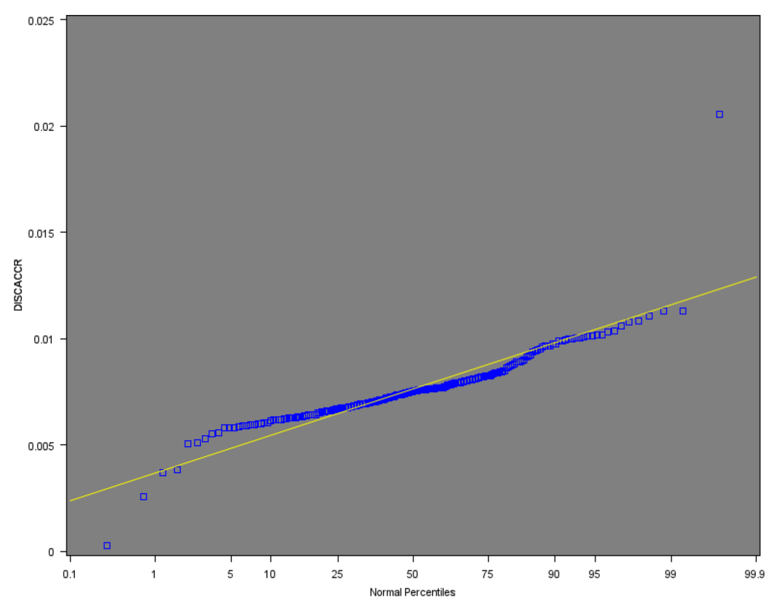




These plots represent the Normal and Lognormal percentiles for the DISCACCR variable in the entire Compustat database sample. As discretionary accruals were taken at their absolute values, values along and beyond the jump observed at the ~97th percentile reflect extreme positive and extreme negative discretionary accruals.

Plots 4 & 5: Histogram and Normal Probability Plot for Sample Discretionary Accruals





These plots depict the distribution and Normal percentiles for the DISCACCR variable in the customer-supplier sample. Both exhibit behavior similar to that of the entire Compustat database sample.

Table 2: One-Sample t-Test of Variable DISCACCR

N	Mean	Std Dev	Std Err	Minimum	Maximum
219	0.00763	0.00170	0.000115	0.000283	0.0205

Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0.00763	0.00740	0.00786	0.00170	0.00156	0.00188

DF	t Value	Pr > |t|
218	-2.80	0.0055

This series of tables depicts results for the One-Sample t-Test of the DISCACCR variable in the customer-supplier sample. Based on the p-value, it can be concluded that the DISCACCR values in the customer-supplier sample do not significantly differ from the DISCACCR values in the entire Compustat database sample. Therefore, the sample is appropriate to use.

Table 3: Summary Statistics of DISCACCR, MJBEPS, and MJBNI

AAER_BEFORE	AAER_DURING	AAER_AFTER	N Obs	Variable	Mean	Std Dev	Minimum	Maximum	N
0	0	1	73	DISCACCR	0.0072765	0.0016689	0.000283026	0.0103339	73
				MJBNI	0.1506849	0.3602173	0	1.0000000	73
				MJBEPS	0.2602740	0.4418206	0	1.0000000	73
	1	0	73	DISCACCR	0.0077512	0.0012696	0.0050733	0.0113055	73
				MJBNI	0.0136986	0.1170411	0	1.0000000	73
				MJBEPS	0.2876712	0.4558098	0	1.0000000	73
1	0	0	73	DISCACCR	0.0078671	0.0020445	0.0050931	0.0205472	73
				MJBNI	0.0684932	0.2543383	0	1.0000000	73
				MJBEPS	0.2328767	0.4255894	0	1.0000000	73

This table displays the summary statistics for the DISCACCR, MJBEPS, and MJBNI variables in the years before, during and after the announcement of a supplier AAER. Each time period contains one observation from each customer-supplier relationship.

Table 4: Summary Statistics for DISCACCR by 2-Digit SIC Industry Group

Analysis Variable : DISCACCR						
CSIC2	N Obs	Mean	Std Dev	Minimum	Maximum	N
16	3	0.0065896	0.000147054	0.0064304	0.0067203	3
20	3	0.0074712	0.000098191	0.0073604	0.0075472	3
28	9	0.0069037	0.000934717	0.0050931	0.0083914	9
29	6	0.0100285	0.000465147	0.0094882	0.0108153	6
33	12	0.0098865	0.0036007	0.0068120	0.0205472	12
35	27	0.0068767	0.0011406	0.0037160	0.0084024	27
36	18	0.0074467	0.000595630	0.0064224	0.0087793	18
37	27	0.0074536	0.000650671	0.0064192	0.0087341	27
38	9	0.0074838	0.000642135	0.0063075	0.0082688	9
42	3	0.0101438	0.0020245	0.0078062	0.0113198	3
45	3	0.0063189	0.000874178	0.0055093	0.0072458	3
48	15	0.0076656	0.0025061	0.000283026	0.0110482	15
49	15	0.0097823	0.000345774	0.0091611	0.0103381	15
50	18	0.0066681	0.0014926	0.0025526	0.0094004	18
51	15	0.0069036	0.000724988	0.0059652	0.0082223	15
53	3	0.0087252	0.000266698	0.0084311	0.0089514	3
54	3	0.0080675	0.000371833	0.0076771	0.0084174	3
57	6	0.0066394	0.0014190	0.0038331	0.0075830	6
59	15	0.0075498	0.0010631	0.0052869	0.0089137	15
73	6	0.0071198	0.000299944	0.0066491	0.0074596	6
99	3	0.0063390	0.000183264	0.0062114	0.0065490	3

This table displays the summary statistics for the DISCACCR variable grouped by customer 2-digit SIC code. All included industry groupings are specific to tangible goods only (i.e. no 2-digit SIC codes beginning with a '6' or '8').

Table 5 & Plot 6: Regression Results for DISCACCR

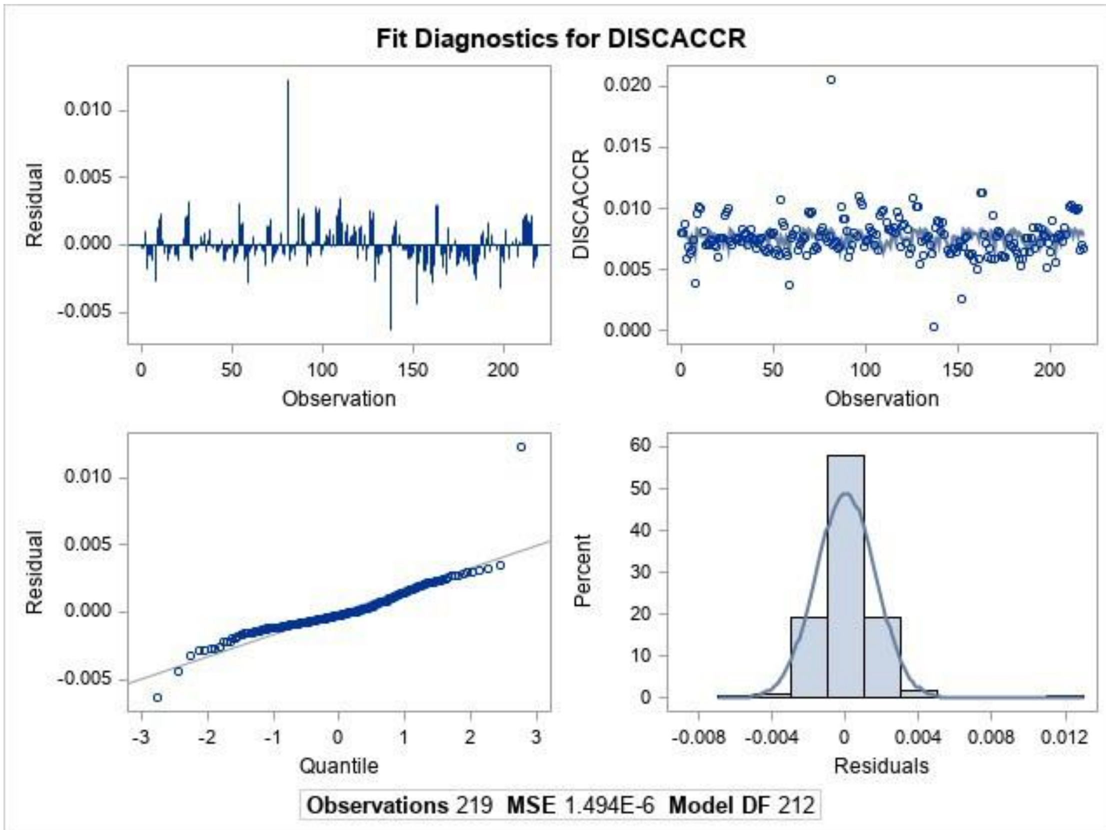
Fit Statistics			
SSE	0.0003	DFE	212
MSE	0.0000	Root MSE	0.0012
R-Square	0.0738		

Variance Component Estimates	
Variance Component for Cross Sections	1.298E-6
Variance Component for Error	1.471E-6

Hausman Test for Random Effects			
Coefficients	DF	m Value	Pr > m
6	6	8.29	0.2176

Parameter Estimates						
Variable	DF	Estimate	Standard Error	t Value	Pr > |t|	Label
Intercept	1	0.008472	0.000794	10.67	<.0001	Intercept
AAER_DURING	1	-0.00008	0.000203	-0.39	0.6978	
AAER_AFTER	1	-0.00055	0.000203	-2.72	0.0070	
SIZE	1	-0.00002	0.000085	-0.28	0.7786	
ROA	1	-0.00089	0.00170	-0.52	0.6029	
LEV	1	-0.00011	0.000180	-0.63	0.5315	
BTM	1	-0.00098	0.000450	-2.18	0.0301	

These tables present the regression results for the DISCACCR variable, using AAER_BEFORE as the reference group. SIZE, ROA, LEV, and BTM serve as control variables.



These plots present goodness-of-fit visualizations for the DISCACCR regression model. The MSE value implies a relatively strong model fit for the DISCACCR variable. Residuals exhibit normal behavior.

Table 6: Regression Results for MJBEPS

GEE Fit Criteria	
QIC	254.1571
QICu	253.0547

Analysis Of GEE Parameter Estimates						
Empirical Standard Error Estimates						
Parameter	Estimate	Standard Error	95% Confidence Limits		Z	Pr > |Z|
Intercept	1.6439	0.9914	-0.2992	3.5871	1.66	0.0973
AAER_DURING	-0.2872	0.3497	-0.9726	0.3982	-0.82	0.4115
AAER_AFTER	-0.1467	0.3730	-0.8778	0.5844	-0.39	0.6941
ROA	-4.6304	2.0371	-8.6230	-0.6378	-2.27	0.0230
BTM	1.6079	0.6252	0.3826	2.8333	2.57	0.0101
SIZE	-0.0431	0.1012	-0.2414	0.1552	-0.43	0.6701
LEV	-0.1136	0.2384	-0.5808	0.3536	-0.48	0.6338

Score Statistics For Type 3 GEE Analysis			
Source	DF	Chi-Square	Pr > ChiSq
AAER_DURING	1	0.67	0.4121
AAER_AFTER	1	0.15	0.6944
ROA	1	3.57	0.0589
BTM	1	7.66	0.0056
SIZE	1	0.18	0.6732
LEV	1	0.25	0.6182

These tables present the regression results for the MJBEPS variable, using AAER_BEFORE as the reference group. SIZE, ROA, LEV, and BTM serve as control variables.

Table 7: Regression Results for MJBNI

GEE Fit Criteria	
QIC	120.7082
QICu	122.1165

Analysis Of GEE Parameter Estimates Empirical Standard Error Estimates						
Parameter	Estimate	Standard Error	95% Confidence Limits		Z	Pr > |Z|
Intercept	3.1955	1.3411	0.5670	5.8241	2.38	0.0172
AAER_DURING	1.6639	0.9335	-0.1658	3.4935	1.78	0.0747
AAER_AFTER	-0.8625	0.5663	-1.9724	0.2473	-1.52	0.1277
SIZE	-0.0741	0.1224	-0.3140	0.1657	-0.61	0.5447
ROA	1.8215	2.8709	-3.8054	7.4484	0.63	0.5258
LEV	-0.1656	0.2187	-0.5942	0.2631	-0.76	0.4490
BTM	-0.0653	0.8247	-1.6816	1.5510	-0.08	0.9369

Score Statistics For Type 3 GEE Analysis			
Source	DF	Chi-Square	Pr > ChiSq
AAER_DURING	1	3.93	0.0474
AAER_AFTER	1	2.34	0.1261
SIZE	1	0.35	0.5520
ROA	1	0.38	0.5356
LEV	1	0.60	0.4379
BTM	1	0.01	0.9371

These tables present the regression results for the MJBNI variable, using AAER_BEFORE as the reference group. SIZE, ROA, LEV, and BTM serve as control variables. "BEV" and its results were cut off from the Type 3 GEE Analysis output. The results of BEV were as follows: DF = 1, Chi-Square = 0.01, Pr > ChiSq = 0.9371.

Table 8: Regression Results for DISCACCR - Lower 50% of Customers by Size

Variance Component Estimates	
Variance Component for Cross Sections	2.089E-6
Variance Component for Error	8.217E-7

Hausman Test for Random Effects		
DF	m Value	Pr > m
6	4.29	0.6377

Parameter Estimates

Variable	DF	Estimate	Standard Error	t Value	Pr > |t|	Label
Intercept	1	0.008516	0.00156	5.46	<.0001	Intercept
AAER_DURING	1	0.00015	0.000218	0.69	0.4933	
AAER_AFTER	1	-0.00038	0.000229	-1.68	0.0960	
SIZE	1	-0.00011	0.000207	-0.51	0.6104	
ROA	1	0.001989	0.00229	0.87	0.3872	
BTM	1	-0.00093	0.000617	-1.51	0.1356	
LEV	1	0.000261	0.000255	1.02	0.3092	

This table shows one-way random effect regression results for the DISCACCR variable, using a subsample of customers sized below the 50th percentile.

Table 9: Regression Results for DISCACCR - Upper 50% of Customers by Size

Variance Component Estimates	
Variance Component for Cross Sections	6.426E-6
Variance Component for Error	1.778E-6

Hausman Test for Random Effects		
DF	m Value	Pr > m
6	3.71	0.7156

Parameter Estimates						
Variable	DF	Estimate	Standard Error	t Value	Pr > |t|	Label
Intercept	1	0.007391	0.00277	2.67	0.0087	Intercept
AAER_DURING	1	-0.00026	0.000262	-1.01	0.3160	
AAER_AFTER	1	-0.00047	0.000270	-1.72	0.0873	
SIZE	1	0.000097	0.000277	0.35	0.7281	
ROA	1	-0.00145	0.00359	-0.41	0.6862	
BTM	1	-0.00091	0.000911	-1.00	0.3174	
LEV	1	-0.00032	0.000235	-1.38	0.1705	

This table shows one-way random effect regression results for the DISCACCR variable, using a subsample of customers sized at or above the 50th percentile.