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Asset Volatility and Financial Sustainability

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Abstract

This study aims to observe companies' sustainability with fundamental-based volatility measures. We use delisting as a proxy to observe how asset volatility can interact with abnormal earnings fluctuation to impact firms' sustainability. Abnormal assets and earning volatility are signals of risk. Accounting literature documented evidence that earnings management can hide severe risks with abnormal asset fluctuation. This paper uses a PCA logistic regression model to predict companies' delisting. We borrow the Six Sigma methodologies to measure the volatility of financial statement items. Then the PCA analysis reduces the data dimensions to twelve factors. The following logistic regression with the panel data provides significant evidence for this prediction. The result shows that assets' abnormal fluctuation is a risk signal concurring with the earnings management literature. One takeaway for accounting policymaking is that companies must disclose detailed explanations if asset volatility is beyond a red line. As SFAS 151 requires direct disclosure of abnormal excess capacity costs, companies must disclose abnormal asset volatility. The paper contributes to accounting literature from two perspectives. First, this paper captures firms' sustainability from the accounting perspective with fundamental measures from quarterly financial reports. It provides a comprehensive way to detect inherent risks. Second, the PCA logistic regression model offers a comprehensive analysis to derive useful information from many attributes, and it can avoid multiple col-linearity issues.

Keywords: Financial Sustainability, Companies' Delist, Six Sigma Metrics, Earnings Manipulation, PCA Logistic Regression

1. Introduction

This paper aims to observe companies' sustainability with fundamental financial statement information. Accounting information is useful for decision-making because it must keep track of an organization's economic resource flow over time with full, consistent, and accurate records. The accounting mechanism makes the information flow within the system and can be traced after the resources enter the accounting loop. However, GAAP allows accounting information to have discretions to deal with uncertainty. These discretions allow accountants to smooth earnings by fluctuating assets (Dechow & Schrand, 2004). This study uses comprehensive data analytics to filter performance from earning management and signal potential sustainability risks. The analysis derives factor measurement from financial statement items to predict companies' sustainability.

In the cyclical accounting loop, assets are the critical bridge within the accounting information reporting system. The accounting logic is straightforward, but the definition from the GAAP and FASB does not clearly enough distinguish assets from expenses. This vagueness leads to the challenges of justifying the recognition of assets that have little relevance to an assessment of the financial position of an enterprise (Scheutez, 1993; Samuelson, 1996). The ambiguity unavoidably leads to discretion in accounting regulations, especially rule-based ones. In the GAAP framework, managers have discretions in classifying and summarizing economic transactions (Zhou et al., 2022). Earnings management literature documents many issues in accounting practice and regulations. The relationship between firms' value and annual earnings has decreased (Dechow & Schrand, 2004).

A general introduction to the theoretic mechanism of earnings can help recall the nature of earnings management. Assets are the economic resources that act as costs awaiting assignment to future revenues (Paton & Littleton, 1994). A balance sheet is a sheet of balances created as a by-product of the matching process (Dechow & Schrand, 2004). All assets will become expenses to match revenues, and by doing so, assets can demonstrate the nature which leads to future benefits. The literature has a tremendous amount of research that claims managers take the discretions to manipulate earnings for their interest. In this research branch, much evidence can pervasively show managers use accounting accruals to boost or smooth earnings (Zimmerman et al., 1988; Jones, 1991; Dechow, 1995; Dechow & Dichev, 1996; Sloan et al., 2001). These studies mostly focused on the income statement and the abnormality in earnings with revenues and expenses.

Information users cherish earnings more than other items. Ross (1977) proposed the famous signal theory. The seminar paper claimed that company management benefits from the information they have and give to investors. Information is a valuable tool for investors and can be known about the company's current state, past, or prospects. The available information must be relevant, accurate, timely, and complete. Earnings are the "bottom line" and are widely believed to be the premier information item in financial statements. Economic theory ascribes corporate earnings as a signal optimally directing resource allocation in capital markets (Lev, 1989; Beneish, 2001). This trend pressures company management to provide smooth earnings to signal the companies' future sustainability. Earnings management tries to take advantage of the directions from GAAP to report smooth earnings when genuine business operations suffer volatility. One frequently used strategy is to use assets' abnormal volatility to smooth earnings. These behaviors were coined as real earnings management or accounting-generated earnings smooth (Dechow & Schrand, 2004; Roychowdhury, 2006).

This study uses comprehensive data analytics to filter accounting-generated earnings performance and signal potential sustainability risks. The paper uses companies' delisting as a proxy of companies' sustainability. From a long-term perspective, this accounting-generated sustainability (real-activity earning management or accrual-based earnings management) can be separated from real corporates' sustainability.

2. Literature Review

2.1. Earnings Manipulation and Assets Volatility

Prior research documents evidence that management manages earnings to meet stakeholders' expectations. There is a discontinuity of current around zero earnings and the previous year's earnings (Hayn, 1995; Burgstahler & Dichev, 1997; Degeorge, Patel & Zeckhauser, 1999; Jacob & Jorgensen, 2007). This discontinuity is interpreted as evidence of earnings management by firms just to meet or slightly beat earnings benchmarks. The literature documents three main motives to manipulate earnings: contractual motivations, capital market impacts, and implying hints to stakeholders. Bounded rationality theory implies that the capital market influences firms' stock values by firms' earnings as a signal. These motivations show that most manipulation behaviors aim to show a steady firm's performance, called "smooth reported income" in the literature (Copeland, 1968, pp 101). Even though these behaviors have different actions, the common goal is to use the discretions from the GAAP, or take fraudulent actions, to report a steady firm's performance, in their interest (Zimmerman & Watts, 1986).

Earnings quality is a theoretical construct, and it shows that GAAP allows managers to adjust how to report their operational results. This study treats earnings manipulation as an abstract concept, not some specific actions. The literature documents two kinds of earnings manipulation: The first is accrued-based earnings manipulation (Jones, 1991; Dechow et al., 1998, 2006; etc.). The second is real earnings manipulation (Cohen et al. 2008, 2011). We cannot have a one-fit-all regulation to stop earnings manipulation because the manipulation strategy is dynamic. Managers can always have an innovative scheme to avoid violating regulations. The regulations delegated by SOX (2002) are mostly related to accrual-based earnings management. While pro-regulatory theorists argue that stronger regulation is needed to solve the manipulation issues, Ribstein (2002) stated that regulation cannot offer a solution. The regulatory changes or new regulation (e.g., the Sarbanes-Oxley Act of 2002) may trigger firms to switch from one mechanism, i.e., accrual-based earnings management, to a new method, say real "earnings-management techniques" (Cohen et al., 2008, p. 759). The new methods likely can be more costly to shareholders and are harder to detect.

When we trace the earnings manipulation over a lengthy period, whatever the manipulation mechanisms the managers would take, the dynamic path of asset changes must have high abnormal fluctuation features. The literature demonstrated similar research results. Francis et al., (1996) provided two pieces of evidence consistent with a strategic element to the timing of special charges. First, they documented that write-offs follow poor abnormal stock return performance. Second, they found that crucial management changes occur concurrently with asset write-offs (including goodwill, PP&E), and restructuring charges but not with inventory write-offs. Correia et al., (2018) documented that asset volatility is significantly positively associated with the probability of bankruptcy from creditors' perspective. Moreover, the robust evidence shows that these fundamental volatility measures improve out-of-sample and help explain cross-sectional variation in credit spreads.

Beneish (1999) proposed a concept of asset quality index (AQI), which is calculated as the ratio of non-current assets other than property plant and equipment (PP&E) to total assets in a given year. The AQI "captures distortions in other assets that can result from excessive expenditure capitalization" (Beneish et al., 2013, p. 76) and quantifies "the proportion of total assets for which future benefits are potentially less certain" (Beneish, 1999, p. 26). High AQI values could signal a company's increased involvement in cost deferral by shifting expenses onto its fixed assets.

To observe how abnormal assets' volatility impacts firms' sustainability, Richardson et al., (2010) called studies that can utilize contextual information such as industry, sector, and macro-environmental data to forecast future earnings, cash flow, risk, and value. They also called for research to exploit the wealth of information contained in general-purpose financial reports. My paper documents evidence using industrial-based assets and earnings volatility to observe how the information in financial statements can predict companies' sustainability with delisting as a proxy.

2.2. Delisting stocks

It is a signal of unsustainability when companies delist from the stock market. Macey et al., (2008) documented quantifiable evidence that the share prices of delisting companies fall by half, percentage spreads on average triple, and volatility almost doubles when delisting occurs. Fungáčová & Hanousek (2011) explained that there are two types of delisting: voluntary and involuntary. A company's voluntary delisting is intentional or, at their request, removing the shares from the capital market index, or the stock market is executed. In this case, the company decides to change the form of a company from a publicly listed company or go public to a limited company. The decision must get approval from at least 75% of the shareholders' meeting. Involuntary delisting is also called compulsory delisting. It is the issuance of stock from the market index capital, and it is not based on the decision of the issuing company. The capital market authorities and regulations decide to exclude a company's shares from the stock index (Bakke et al., 2012). This study focuses on the second type, which signals that the delisting companies have issues with sustainability. The delisting companies were on the list of COMPUSTAT from 2006 through 2019 but cannot be found on the list at the end of 2019. A follow-up check confirms a firm is a delisting company if Yahoo Finance shows the company is a private company with a price lower than one dollar or is merged into other firms. The delisting risk could come from an operational loss or a management's strategic earnings manipulation.

3. Methodology

3.1. Hypothesis Development

This paper proposes a novel approach to observing assets' abnormal fluctuation. The rationale is that all assets will become expenses. The nature of aggressive earning management behaviors (sometimes bad even fraud activities) is to manipulate the fluctuation level or the speed of this transformation. One essential feature of earnings management is that manipulated earnings must be reversed in future years. Because of this accounting mechanism, the manipulation will be reflected in the signals of abnormal fluctuation of asset change no matter the manipulation approaches management use. Assets' abnormal fluctuation is considered an indicator of risk. The risk could be inherent risk regarding business operations, and it also may be a control risk regarding how a company uses internal controls to supervise aggressive earnings management. When a company suffers decreased operating earnings, management has pressure and motivation to smooth earnings. If the firm's internal control is weak, management can manipulate earnings by fluctuating other financial accounts, like assets. This study uses financial statement information to retrospectively observe whether abnormal asset fluctuation can and how it can lead to earnings management and sustainability risks.

There is a closed loop between assets and expenses; the assets (long-term or short-term accruals) will fluctuate when management uses non-normal-operating ways to make earnings persistent and smooth. This notion is expressed as Continuity Equation (CE hereafter) in the auditing area (Allies et al., 2006; Kogan et al., 2014). CE is a mathematical expression often used in physics to express various conservation laws. Allies et al. (2006) borrow this term to construct audit benchmarks that can capture the dynamics of the fundamental business process of a firm. They claimed, "In the CE metaphor, each business process is analogous to a control volume made up of a variety of transaction flows, or business activities. If transaction flows into and out of each business process are equal, the business process would be in a steady-state, free from anomalies. Otherwise, if spikes occur in the transaction flows, the steady state of the business process cannot be maintained." Kogan et al., (2014) take three mathematical equations, including a simultaneous equation, a vector autoregressive model, and a linear regression model, to capture the anomalies on the transactional data level. Once a tendency is set in motion in closed conditions, it must be fulfilled.

A business's abnormal assets' fluctuation captures its excessively volatile operations. Many factors could cause the abnormal fluctuation of assets. Some external factors can lead to this abnormal fluctuation, e.g., transformative technologies can lead to some assets being obsolete. Another example is that the pandemic significantly changed many supply-chain ecosystems, leading to abnormal asset fluctuation. Some internal factors, e.g., operational difficulty or earnings management, can also lead to this abnormal asset fluctuation. These internal factors, operational difficulty, or earnings management can capture and signify the company's inherent risk and sustainability.

It is ultimately an empirical question as to whether and how measures of asset volatility derived from financial statement data can predict companies' sustainability. This empirical observation does not explain the detailed earnings manipulation schema but the indicator-oriented signal to push companies to provide extra disclosure for their abnormal fluctuation. By doing so, we can improve information quality.

Based on the discussions above, two hypotheses can be developed:

H1: When management uses the fluctuation of assets to smooth earnings, asset fluctuation has a negative relationship with the fluctuation of earnings.

H2: An abnormal long-term asset fluctuation is highly related to the firms' sustainability.

This paper takes two studies to observe how asset volatility interacts with earnings volatility and impacts company delisting risk.

3.1. Define the volatility metrics.

The first stage is to define the assets and earnings volatility. Literature uses normalization to measure volatility (e.g., Correia et al., 2018). This study uses Six Sigma metrics from the manufacturing industry and quality management to measure fluctuation and volatility. More and more management use Six Sigma measurements to improve business performance. As Anil et al. (2004) demonstrated, "[the] integration of Six Sigma techniques brings in the rigor, thoroughness, and visibility to program management and thus provide a competitive edge resulting in an improved business outcome, resulting cost/cycle time reduction and increase in customer satisfaction."

The volatility metrics are defined based on the balance change between two consecutive quarterly balances. The study defines the change of accounting item as Equation 1:

$$AccountingItemChange_{i,t} = (AccountingItem_{i,t} - AccountingItem_{i,(t-1)}) / AccountingItem_{i,(t-1)}$$

*notes: i means a specific company, and t means a specific quarter.

Equation 1

This study defines the volatility of the balance change with an absolute Z-score. As discussed in Section 2. Some earnings management schema just moves revenue ahead and delays expenses later, and it will be adjusted back in the following years. Thus, the average volatility will weaken the fluctuation level over a long-term period. The absolute Z-score can solve this dilemma and signify this volatility. The volatility metrics of a time series are defined in Equation 2 below.

$Abs\_Z\text{-}score\_TimeSeries\_AccountingItemChange_{i,t} =$

|(AccountingItemChange$_{i,t}$ -Mean of the time series)|/ Standard Deviation of the time series

*notes: i means a specific company, and t means a specific quarter.

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Equation 2

This study uses the first two digits of the Standard Industrial Classification (SIC) to identify the major industry group. The study uses the same approach to define absolute Z-score accounting item change across the industry in Equation 3 below:

Abs_Z-score_Industry_AccountingItemChange$_{i,t}$ =

|(AccountingItemChange$_{i,t}$ -Mean of the industry)|/ Standard Deviation of the industry

*notes: i means a specific company, and t means a specific quarter.

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Equation 3

We select Current Asset, Other Asset, Total Asset, PP&E, Working Capital, EPS Including Extraordinary Items, EPS from Operations, and Revenue as eight accounting items to observe how their volatility can impact firms' delisting. The study extracted the data sample from COMPUSTAT from 2006 through 2021. The original dataset includes 318,782 firm quarters. The author keeps the firms with more than 12 quarters to ensure the time-series data can be statistically meaningful. After this cleansing, the final dataset includes 6,218 firm years (24,800 firm quarters). Using the above-mentioned equations, the study computes the volatility metrics (absolute Z-score) for each quarter during these 16 years. The annual average was calculated as the data input for the following analysis. The study also includes the maximum value of the four quarters as another metric to illustrate the abnormal fluctuation of the balance changes. The maximum metrics capture earning management behavior by writing off an abnormal amount of assets in one quarter (usually the fourth quarter) (Francis et al., 1996). Delisted companies are defined as listed companies from 2006 and were delisted from 2007 through 2019. This is a binomial variable, and "1" is a delisted company. "0" is normal. The study first compared the COMPUSTAT data from 2006 and 2019 to extract the firms in 2006 but not 2019. Then the author confirmed these are delisted companies by searching Yahoo Finance data. These companies were private or merged with others, or the price was under one dollar in 2019. The author keeps two types of metrics, including time-series scaled and industry-scaled, in the research. The description of the annual average volatility metrics and the statistics are illustrated in Table 1.1.

Table 1. Data Attributes and the Statistics Description (observations: 6218)

Variable	Description	Average	Std. Dev.	Variable	Description	Average	Std. Dev.
X1	Annual average of the quarterly Current Assets volatility metrics (scaled by time series).	0.68	0.43	X17	Annual maximum of the quarterly Current Assets volatility metrics (scaled by time series).	1.28	0.94
X2	Annual average of the quarterly Other Assets volatility metrics (scaled by time series).	0.51	0.49	X18	Annual maximum of the quarterly Other Assets volatility metrics (scaled by time series).	1.1	1.35
X3	Annual average of the quarterly Total Assets volatility metrics (scaled by time series).	0.58	0.45	X19	Annual maximum of the quarterly Total Assets volatility metrics (scaled by time series).	1.14	1.09
X4	Annual average of the quarterly Working Capital volatility metrics (scaled by time series).	0.49	0.52	X20	Annual maximum of the quarterly Working Capital volatility metrics (scaled by time series).	1.17	1.16
X5	Annual average of the quarterly PP&E volatility metrics (scaled by time series).	0.95	1.64	X21	Annual maximum of the quarterly PP&E volatility metrics (scaled by time series).	1.65	3.53
X6	Annual average of the quarterly EPS of Operations volatility metrics (scaled by time series).	4.4	34.32	X22	Annual maximum of the quarterly EPS of Operations volatility metrics (scaled by time series).	9.14	56.28
X7	Annual average of the quarterly EPS Including Extraordinary Items volatility metrics (scaled by time series).	0.53	0.49	X23	Annual maximum of the quarterly EPS Including Extraordinary Items volatility metrics (scaled by time series).	1.14	1.3
X8	Annual average of the quarterly Revenue volatility metrics (scaled by time series).	0.87	4.12	X24	Annual maximum of the quarterly Revenue volatility metrics (scaled by time series).	1.58	4.33
X9	Annual average of the quarterly Current Assets volatility metrics (scaled by the first two digits SIC group).	0.53	0.5	X25	Annual maximum of the quarterly Current Assets volatility metrics (scaled by the first two digits SIC group).	0.99	0.98
X10	Annual average of the quarterly Other Assets volatility metrics (scaled by the first two digits SIC group).	0.4	0.51	X26	Annual maximum of the quarterly Other Assets volatility metrics (scaled by the first two digits SIC group).	0.85	1.29
X11	Annual average of the quarterly Total Assets volatility metrics (scaled by the first two digits SIC group).	0.48	0.5	X27	Annual maximum of the quarterly Total Assets volatility metrics (scaled by the first two digits SIC group).	0.94	1.07
X12	Annual average of the quarterly Working Capital volatility metrics	0.43	0.58	X28	Annual maximum of the quarterly Working Capital volatility metrics	0.85	1.22

	(scaled by the first two digits SIC group).				(scaled by the first two digits SIC group).		
X13	Annual average of the quarterly PP&E volatility metrics (scaled by the first two digits SIC group).	0.59	0.4	X29	Annual maximum of the quarterly PP&E volatility metrics (scaled by the first two digits SIC group).	1.14	0.83
X14	Annual average of the quarterly EPS of Operations volatility metrics (scaled by the first two digits SIC group).	0.48	0.49	X30	Annual maximum of the quarterly EPS of Operations volatility metrics (scaled by the first two digits SIC group).	1.00	1.26
X15	Annual average of the quarterly EPS including Extra Items volatility metrics (scaled by the first two digits SIC group).	0.83	3.57	X31	Annual maximum of the quarterly EPS including Extra Items volatility metrics (scaled by the first two digits SIC group).	2.36	14.16
X16	Annual average of the quarterly Revenue volatility metrics (scaled by the first two digits SIC group).	0.53	0.52	X32	Annual maximum of the quarterly Revenue volatility metrics (scaled by the first two digits SIC group).	0.97	1.02
Delist	This is a binomial variable, and “1” means delisted. “0” means normal. Delisted companies are defined as the companies listed from 2006 through 2008 and were delisted from 2009 through 2018.	0.2	0.4				

3.2. A test for the relationship between earning volatility and assets volatility

The question from Hypothesis 1 aims to test whether management uses the fluctuation of assets to smooth earnings. The study assumes that asset fluctuation has a negative relationship with earnings fluctuation. Assets are the economic resources that act as costs awaiting assignment to future revenues (Paton & Littleton, 1994). Assets will sooner or later become expenses to match revenues and lead to future benefits. When the revenues face volatile fluctuation, management has the discretion to fluctuate the asset side (reflected in the expense side) to smooth earnings. The abnormal fluctuation in assets balance will be reversed in the following years (Beneish, 1999; Correia et al., 2018). It is challenging, if not impossible, to detect some strategic earnings management because accounting is based on many assumptions and estimates. To achieve this goal, managers may aggregate various transactions via various accounts, like inventory, leased assets, and accounts receivable. Some of them are real business transactions, and some of them just take advantage of accruals. However, these behaviors unavoidably will be reflected in the fluctuation level of asset balances. An abnormal asset fluctuation signals inherent risk (huge fluctuation of revenues) or control risk (lack of internal controls to assure earnings quality).

This test sets two groups of regressions to observe how the assets' volatilities impact earnings volatilities. Each group has three regressions. The first group includes three dependent variables include EPS of Operation Average (X14), EPS including Extra Items Average (X15), and Revenue Average (X16). The independent variables have the asset volatility metrics items, including the average and maximum volatility metrics. The result is illustrated in Table 2 below.

The results show that working capital volatility metrics have a significant positive relationship with three earning volatility metrics. The fluctuation of earnings metrics moves in the same direction. However, in Regression 3, the working capital volatility maximum metric shows a significant negative relationship with Revenue metrics. This negative relation demonstrates that firms have the potential to fluctuate working capital to smooth earnings when revenue faces a challenging fluctuation. The regression of EPS of operation (Regression 1) shows a positive relationship with the maximum volatility metrics of PP&E but a negative relationship with the average volatility metrics of PP&E. This finding demonstrates that a highly volatile PP&E change can smooth the change of the EPS of Operation. The highly fluctuated EPS of operation is responded to by a highly fluctuated PP&E in one quarter (usually the fourth quarter) of the studying year. Francis et al. (1996) and Beneish (1999) had equivalent results: firms manage earnings by writing off assets or restructuring charges but not with inventory write-offs. Regression 2 shows a positive relationship between EPS including extra items and the average volatility metrics of other assets and working capital. No evidence regarding earnings smoothing can be found in this regression.

Table 2. The Regression Result of Earnings and Assets Volatility (Average Metrics)

Dependent Variable	Regression 1		Regression 2		Regression 3	
	X6 (EPS of Operation Average)		X7 (EPS including Extra Items Average)		X8 (Revenue Average)	
R-squared	0.01		0.02		0.005	
Variable	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Current Asset Average (X1)	2.37	1.96*	(0.02)	(0.37)	0.29	0.97
Other Asset Average (X2)	(2.67)	(1.9)	0.12	2.61**	(0.32)	(2.7)**
Total Asset Average (X3)	(1.51)	(0.85)	0.07	1.22	(0.44)	(1.55)
Working Capital Average (X4)	2.62	4.46***	0.05	2.11*	0.59	12***
PP&E Average (X5)	(1.5)	(4.59)***	0.003	0.24	(0.06)	(1.31)
Current Asset Max (X17)	0.26	0.38	0.009	0.47	0.05	0.38
Other Asset Max (X18)	1.81	3.1***	(0.02)	(1.47)	0.1	1.82
Total Asset Max (X19)	(1.48)	(2.08)*	0.005	0.25	0.17	1.27
Working Capital Max (X20)	(0.29)	(0.66)	0.0004	0.04	(0.29)	(3.51)***
PPE Max (X21)	0.59	3.82***	0.0009	0.16	0.03	1.44
Constant	3.48	8.08***	0.42	29.06***	0.8	7.81***

The second group of regression includes dependent variables of the EPS of Operation Maximum (X22), EPS including Extra Items Maximum (X23), and Revenue Maximum (X24). The independent variables stay the same as the study did in the first group of regressions. The result is illustrated in Table 3 below.

Two findings are highlighted in this test. First, the maximum volatility of these earnings items has a positive relationship with the average volatility of PP&E but a negative with the maximum volatility of PPE. This finding concurs with the findings in the first test. The result means highly fluctuated PP&E balances often relate to a smooth EPS performance. When the earning items have abnormally high volatility in any quarter, PP&E will also have a high responding fluctuation. Second, regression 3 shows a negative significant relationship between the maximum volatility metrics of revenue and the average volatility of other assets, total assets, working capital, and PPEs. When firms face abnormally fluctuating revenues for any reason, firms are highly likely to fluctuate asset balances to fluctuate expenses and smooth earnings (could be reflected as EPS or other earnings items). Furthermore, the relationship is negative between the maximum volatility metrics of revenue and the maximum volatility of total assets. This relationship shows that a highly fluctuated revenue usually will be responded to by a highly fluctuated total assets in one quarter of the studying year.

Table 3. The Regression Result of Earnings and Assets Volatility (Maximum metrics)

Dependent Variable	Regression 4		Regression 5		Regression 6	
	X22 (EPS of Operation Maximum)		X23 (EPS including Extra Items Maximum)		X24 (Revenue Maximum)	
R-squared	0.01		0.01		0.007	
Variable	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Current Asset Average (X1)	5.98	1.9	(0.15)	(1.6)	0.52	1.71
Other Asset Average (X2)	(6.33)	(1.7)	0.06	0.74	(0.32)	(2.62)**
Total Asset Average (X3)	(5.62)	(1.16)	0.02	0.22	(0.58)	(1.97)*
Working Capital Average (X4)	5.85	3.91***	0.02	0.38	(0.25)	(3.76)***
PPE Average (X5)	(3.94)	(4.56)***	(0.14)	(4.79)***	(0.2)	(3.47)***
Current Asset Max (X17)	0.98	0.55	0.09	1.95*	0.02	0.16
Other Asset Max (X18)	4.81	3**	0.04	1.15	0.11	1.95
Total Asset Max (X19)	(3.80)	(1.98)*	0.09	1.96*	0.27	2*
Working Capital Max (X20)	(0.33)	(0.28)	0.32	1.35	0.1	1.16
PP&E Max (X21)	1.56	3.85***	0.06	4.38***	0.1	3.82***
Constant	8.08	7.2***	0.93	28.27***	1.29	11.65***

Hypothesis 1 can be supported by the analysis result. Management uses the fluctuation of assets to smooth earnings. When a firm faces a volatile revenue fluctuation because of severe competition or a dawn-warding economic environment, managers have extremely limited discretions to manage the revenue side, so they can manage the expense side and fluctuate the balance of assets.

3.3. A PCA logistic regression to study how the interaction of assets and earnings volatility impact companies' delisting

In this section, the author wants to observe how abnormal assets and earnings fluctuation and the interaction can cause firms to risk. The study uses firms' delisting as a proxy to observe how the volatility metrics can impact firms' sustainability.

3.3.1. Develop the Conceptual Factors with Principal Component Analysis

A logistic regression model is frequently used to predict binomial events (happen or not). One practical issue in this kind of analysis is that logistic regression is extremely sensitive to multiple collinearities. When variables are highly relative, a smaller change in samples can lead to a sweeping change in coefficient estimation and reduce the effect of prediction. However, most financial accounts are mutually related, and the degrees of relativity are often extremely high. An often-used approach to solve this multiple collinearity issue is to remove certain variables from the model, but it would lose especially useful financial information because of the deletion. Han et al., (2008) proposed using PCA logistic regression to solve these issues. In this approach, we must first conduct the PCA analysis on the financial account items and then select certain factor variables according to contribution rates to carry on logistic regression. The PCA analysis can concentrate original variables into a few virtual components with the least information loss. The generated virtual components are not from the original variables directly but are some new factors through new synthesis that can affect the original variables. These generated components are independent statistically, so we can effectively overcome multiple co-linearity among original variables.

Using STATA software, the study runs a PCA analysis of the 32 financial accounting items and obtains initial Eigenvalues and extraction sums of squared loadings (Table 4). The study uses one as the threshold of the eigenvalue. Twelve virtual factors are chosen to test how these factors impact companies delisting. Table 4 shows that the contribution rate of the first six eigenvalues is 87%. The information loss from the original variables is limited to within a controlled range.

Table 4. Total Variances Explained

Rank	Initial Eigenvalues	% of Variance	Cumulative Variance
1	7.06	0.22	0.22
2	2.82	0.09	0.31
3	2.55	0.08	0.39
4	2.34	0.07	0.46
5	2.02	0.06	0.53
6	1.99	0.06	0.59
7	1.96	0.06	0.65
8	1.75	0.05	0.70
9	1.52	0.05	0.75
10	1.34	0.04	0.79
11	1.26	0.04	0.83
12	1.12	0.03	0.87

The author chose a correlation loading significance of 0.25 or above as the threshold for these selected eigenvectors. The component metrics are reported in Table 5.

Table 5. The Component Metrics

	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7	Factor8	Factor9	Factor10	Factor11	Factor12
X1									(0.28)			
X2				(0.25)								
X4				0.28								
X5					0.26	0.55						
X6					(0.27)			0.51				
X7			0.35					(0.34)				0.4
X8						0.32	0.56					
X9	0.27			(0.28)							(0.28)	
X10									0.3			
X11	0.3										(0.26)	
X12				0.36					0.36			
X13										0.54		
X14		0.39										(0.5)
X15					0.53		0.34					
X16		0.3									0.48	
X17	0.25								(-0.26)			
X18				(0.25)								
X19	0.25											
X20				0.33							0.26	
X21					0.25	0.54						
X22					(0.27)			0.5				
X23			0.38					(0.34)				0.37
X24						0.31	0.56					
X25	0.28										(0.26)	
X26				(0.29)					0.3			
X27	0.3											
X28				0.38					0.34			
X29										0.58		
X30		0.37	0.25									(0.49)
X31					0.53		0.35					
X32		0.29							(0.26)		0.5	

Based on the metrics of the component illustrated in Table 5, the study generates the following twelve conceptual components. The Cronbach Reliability Coefficient is 0.64 for these conceptual components, which is acceptable for these virtual components in the literature (e.g., Kocher et al., 2005; Jaracz et al., 2006).

The study defines the first factor as Asset Volatility. The control variables include time-series-scaled Current Asset maximum and Total Asset maximum, Industry-group-scaled Current Asset average and maximum, and Total Asset average and maximum. This factor is expected to affect firms' desilting risk positively. Abnormal asset fluctuation can be a risk signal and lead to companies delisting. This factor can be expressed as:

$$\text{Asset Volatility (Factor1)} = 0.25*X17 + 0.25*X19 + 0.28*X25 + 0.3*X27 + 0.27*X9 + 0.3*X11$$

The study defines the second factor as industry-scaled earnings volatility. The control variables include industry-scaled Revenue (average and maximum) and EPS of Operation (average and maximum). This factor means highly unstable business revenues and is expected to affect firms' delisting risk positively. This volatility may not be accounting-generated fluctuation for two reasons. First, GAAP offers extremely limited discretion in managing sales or revenues, so most earnings management schema is unrelated to revenues. Second, the earnings smooth schema mainly takes the time-series perspective, and few information users care about how the firms' earnings fluctuation differs from the industry peers. The second factor can be expressed as:

$$\text{Industry scaled Earnings Volatility (Factor2)} = 0.37*X30 + 0.29*X32 + 0.39*X14 + 0.3*X16$$

The third factor can be defined as EPS volatility. The control variables include time-series scaled EPS Including Extra Items (average and maximum), and industry-scaled EPS of Operation maximum. This factor is expected to negatively affect delisting risk, which means exceptionally smooth EPS including extra items may be accounting-generated related to high-level earnings manipulation. There are many accounting discretions in the computation of EPS including extra items. The third factor can be expressed as:

$$\text{EPS Volatility (Factor3)} = X7*0.35 + 0.38*X23 + 0.25*X30$$

The fourth factor is defined as Working Capital Corresponding to Other Assets. It has four control variables regarding working capital and four other assets. Both cover average and maximum in the time-series group and industry-scaled group. The working capital group has a negative relationship with the other assets group. The factor can be expressed as:

$$\text{Working Capital Corresponding to Other Assets (Factor4)} = X20*0.33 - X2*0.25 - X18*0.25 - 0.29*X26 + 0.38*X28 + X4*0.28 - 0.28*X10 + 0.36*X12$$

The fifth factor is defined as PP&E Corresponding to EPS. It has two time-series scaled PP&E metrics and two EPS of Operation metrics (average and maximum). The PP&E metrics have a negative relationship with EPS metrics. This negative relationship can be interpreted as evidence that PP&E volatility can smooth the EPS fluctuation, so this component is a primary variable in the following PCA logistic regression. The other two control variables are industry-scaled metrics of EPS including Extra Items. This factor is expected to negatively affect firms' delisting risk because the negative relationship may cancel abnormal fluctuations. We need to check the interaction impact of this factor and other earnings-related factors. The factor can be expressed as:

PP&E Corresponding to EPS (Factor5) =X5 *0.26 -X6*0.27 +X21*0.25-0.27*X22 + 0.53*X31 + 0.53*X15

The sixth factor is defined as PP&E Corresponding to Revenue. It has two time-series scaled PP&E metrics and two Revenue metrics, including average and maximum. The PP&E metrics have a positive relationship with Revenue metrics. This positive relationship concurred with the regression result in the prior section. It is interpreted as evidence that PP&E volatility can smooth earnings when firms face significant revenue fluctuation. Another phenomenon should happen for highly growing companies with fast revenue and PP&E growth. This factor is a primary variable in the following PCA logistic regression, but the direction impacting firms' delisting risk is undecided. The factor can be expressed as:

PP&E Corresponding to Revenue (Factor6) =X5*0.55 +X21*0.54+ X24*0.31+ X8*0.32

The seventh factor is the Interaction of Revenue, Working Capital, and EPS Extra. It has time-series scaled Revenue Maximum metrics, and three industry-scaled metrics (average and maximum EPS including extra; Working Capital maximum). The PP&E metrics have a positive relationship with Revenue metrics. This interaction shows supplemental evidence that firms could use abnormal fluctuation of working capital to inject smooth earnings in EPS including extra items when firms face significant revenue fluctuation. This factor is a primary variable in the following PCA logistic regression and is expected to affect firms' delisting risk negatively. The factor can be expressed as:

Interaction of Revenue Working Capital & EPS Extra (Factor 7) = X24 *0.56 +X31*0.35 + X28*0.56 +X15*0.34

The eighth factor can be defined as Time Series EPS volatility. The control variables include time-series scaled EPS of Operation and EPS Including Extra Items (average and maximum). This component can be expressed as:

Time Series EPS (Factor 8) = X6 *0.51 -X7*0.34 +X22*0.5 -X23 *0.34

The ninth factor is the first interaction of industry scaled Revenue and multiple Assets (a similar interaction is followed in the eleventh component). It has industry-scaled Revenue Maximum metrics and six asset volatility metrics (including Current assets, Other assets, and Working Capital). The Revenue metrics have a positive relationship with Other Asset and Working Capital metrics, but a negative relationship with Current Asset metrics. This interaction shows supplemental evidence that firms could use an abnormal asset fluctuation to smooth earnings when firms face significant revenue fluctuation. This component is another primary variable in the following PCA logistic regression and is expected to negatively affect firms' delisting risk. The component can be expressed as:

First Interaction of Revenue & Multiple Assets (Factor 9) =X26*0.3 - X1*0.28 -X17*0.26 -X32*0.26+ X28*0.34 + 0.3*X10+ X12*0.36

The tenth factor can be defined as industry-scaled PP&E volatility. The control variables include industry-scaled PP&E Volatility (average and maximum). This factor is expected to affect firms' delisting risk positively; the higher PP&E volatility means a higher risk. The tenth component is expressed as:

Industry-scaled PP&E Volatility (Factor 10) = X29*0.58 +X13*0.54

The eleventh factor is the second interaction of industry-scaled revenue and multiple assets. It has industry-scaled Revenue maximum and average metrics and four asset volatility metrics (including Current assets, Total Assets, and Working Capital). The revenue metrics have a positive relationship with working capital maximum metrics, but a negative relationship with current asset and total asset metrics. This interaction shows supplemental evidence that firms could use an abnormal asset fluctuation to smooth earnings when firms face significant revenue fluctuation. This factor is another primary variable in the following PCA logistic regression and is expected to negatively affect firms' delisting risk. The component can be expressed as:

Second Interaction Revenue & Multiple Assets (Factor 11) = X20*0.26 - X25*0.26 +X32 *0.5 -X9 *0.28 -X11*0.26 +X16*0.48

The twelfth factor can be defined as EPS interaction volatility. It is similar to the third component that includes time-series scaled EPS Including Extra Items (average and maximum), and industry-scaled EPS of Operation maximum. However, the difference is that this component adds industry-scaled EPS of Operation average as the fourth control variable and shows a negative relationship between these two groups. This interaction demonstrates the potential that firms could structure a fluctuation of EPS Including extra Items to smooth EPS of Operations. Literature shows evidence that EPS including Extra Items has more accounting discretions to deal with and it is easy for management to take advantage of it (Dechow &

Schrand, 2004; Roychowdhury, 2006). The twelfth component can be expressed as:

EPS Interaction Volatility (Factor 12) = X7*0.4 +X23 *0.37 -X30*0.49 -X14*0.5

The study tests Cronbach's Alpha for these 12 variables; the result is 0.7019, which shows acceptable reliability for these virtual concepts. In the next stage, we can put these concepts into the PCA logistic regression to observe how these volatility metrics can impact the delisting.

3.3.2. The Result of the PCA Logistic Regression

The author runs a PCA logistic regression to observe how abnormal fluctuation impacts companies' sustainability. The study takes the mixed effect logistic regression on the panel data with the 12 latent variables. The study also controls the interaction of factors 5 and 8 and the interaction of factors 5 and 12. The result is reported in Table 6 below.

Table 6. The Report of the PCA Logistic Regression
Dependent Variable: Delist

Variable	Coefficient	Standard Error	Statistics (P-value)	95% CI
Factor 1	(0.02)	0.03	(0.61)	(0.09) - 0.045
Factor 2	0.4	0.06	6.7***	0.28 - 0.51
Factor 3	(0.16)	0.05	(3.04)***	(0.27) – (0.06)
Factor 4	(0.004)	0.01	(0.41)	(0.07) - 0.04
Factor 5	(0.006)	0.008	(0.74)	(0.02) – 0.01
Factor 6	(0.03)	0.01	(2.57)**	(0.05)- (0.006)
Factor 7	(0.001)	0.01	(0.12)	(0.02) – 0.02
Factor 8	(0.19)	0.02	(0.8)	(0.07) -0.03
Factor 9	0.13	0.04	(3.18)***	0.05-0.2
Factor 10	0.04	0.05	0.08	(0.06) – 0.14
Factor 11	(0.14)	0.05	(2.57)**	(0.25) – (0.03)
Factor 12	(0.02)	0.03	(0.68)	(0.09) -0.04
Factor 5* Factor 8	(0.0004)	0.0001	(2.33)**	(0.007)- (0.001)
Factor 5* Factor 12	(0.005)	0.0002	(2.29)**	(0.0009)- (0.0001)
Factor 7* Factor 8	(0.003)	0.0009	(3.1)***	(0.005)- (0.001)
Constant	(1.55)	0.06	(27.11)***	(1.68) – (1.39)

3.3.3. A Discussion of the Analytics Result

According to the results in Table 6, factor 2 significantly affects firms' desilting risks as expected. This positive relationship means that highly fluctuating business revenue causes operating risk. In other words, this risk comes from genuine business operations and competition. The risk caused by this factor is not from earnings management activities. Factor 3 negatively affects delisting risk, which means very smooth EPS including extra items may be accounting-generated related to high-level earnings manipulation. There are many accounting discretions in the computation of

EPS including extra items. Unfortunately, we cannot see a significant relationship between factor 5 and delisting risk. However, the interaction of factors 5 and 8 and factors 5 and 12 significantly impact the delisting risk. This finding concurs with that of Francis et al. (1996) and Beneish (1999). They found that firms manage earnings by writing off long-term assets or restructuring charges but not with inventory write-offs. These writing-offs often happened in the fourth quarter. However, one situation can be excluded as a risky sign. The result of factor 6 demonstrates this exclusion; highly growing companies could have concurrently fast revenue and PP&E growth. The highly volatile PPEs in high-growth companies are normal. Lastly, the two interactions between revenue and multiple assets (Factors 9 and 11) illustrate an earnings management behavior. When firms face business challenges and suffer an abnormal fluctuation in revenues, they have the motivation and discretion to fluctuate their assets balances and smooth earnings to reveal a financial sustainability risk.

However, Factor 1 does not show a significant relationship in the regression. This result is unexpected, and we may explore the potential reasons in future studies. The potential interpretation is that there are two types of asset volatility, including real assets volatility and accounting-generated assets volatility. Most of the real assets' volatility is not a signal of risk. This interpretation is also related to the fourth factor. Working capital is highly liquidated, and the fluctuation is complicated when it corresponds to other assets. We cannot derive potential earning management schema from these current assets' fluctuation.

Based on the discussions above, hypothesis 2 is highly supported. An abnormal long-term asset fluctuation is highly related to the firms' sustainability.

Conclusion

Assets will become expenses to match revenues and recognize earnings sooner or later. The speed of this transformation really matters because many earnings management schemas may be derived from how fast assets can become expenses. This paper uses the Six Sigma metrics to trace earnings manipulation over a lengthy period. The findings show that the abnormal fluctuation of long-term assets signals the risk that companies use accounting-generated earning management to manipulate earnings. Mostly this manipulation is strategic and hard to detect. The PCA regression analysis breaks down the nature of these aggressive earning management behaviors (sometimes bad even fraud activities). This breakdown works because manipulated earnings must be reversed in future years. The manipulation will be reflected in the signals of abnormal fluctuation of asset change no matter the manipulation approaches. Fixed Assets' abnormal fluctuation is considered a clear indicator of risk.

From the policy-making perspective, abnormal fluctuation of assets needs to be alerted, and management is responsible for disclosing the back story of these fluctuations. As SFAS 151 requires direct disclosure of abnormal excess capacity costs, companies have an obligation to disclose abnormal asset volatility. This disclosure can force management away from using long-term assets to manage earnings.

In future research, this topic can be extended to observe whether the abnormal fluctuation is related to share-based compensations and corporate governance features. It is also valuable to explore whether auditing can identify the information contents from the volatility of the abnormal asset in annual auditing. Furthermore, the abnormal asset fluctuation also could be related to share price behavior and third-party stock trading behavior.

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