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Evaluating the Accrual Anomaly with the Decomposition Method

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JEL classification: G12; G14; M41

Keywords: Accruals; Anomalies; Asset pricing; Market efficiency; Arbitrage costs

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1. Introduction

Accruals, an important concept in accounting, reflect the difference between cash-based profitability and accrual-based earnings. In other words, accruals represent the difference between non-cash-based receipts and payments. Sloan (1996) first identifies a significant negative correlation between accruals and the cross-section of size-adjusted abnormal returns, known as the "accrual anomaly." Other researchers, however, have found this negative correlation difficult to explain with the widely used asset pricing models (Fama and French, 2016; Hou et al., 2015; Khan, 2008).

Previous studies attempt to explain the accrual anomaly based on risk (Ball et al., 2016; Desai et al., 2004; Wu et al., 2010), arbitrage costs (Dechow and Ge, 2006; Mashruwala et al., 2006; Sloan, 1996), or naïve investor fixation (Dechow and Ge, 2006; Sloan, 1996). However, no study provides a comprehensive comparison and evaluation of these different theories, to analyze which theory best explains the puzzle. To this end, we adopt the decomposition method proposed by Hou and Loh (2016), which can quantify the explanatory power of each candidate indicator. Using this method, we compare and evaluate the various existing explanations and identify the theory that best explains the accrual anomaly. More importantly, by quantifying the contribution of each explanation, we can assess the overall progress of research to date, and provide a reference for future research and investment applications.

To guide our research, we classify the existing explanations into two groups. The first group includes the risk-based explanations, which are based on the efficient market hypothesis and modifies the asset pricing model by adding several alternative risk factors such as the value premium, investment, and cash-based operating profitability. Desai et al. (2004) argue that discretionary accruals are positively related to forecasted growth and that the accrual anomaly is a manifestation of the value-glamour anomaly. Hence, they suggest that measures of value should be included in the asset pricing model. In this paper, we use cash flows from operations scaled by price (*CFO/P*) as the measurement for value. Wu et al. (2010) argue that the accrual anomaly happens due to an attribute of investments known as the diminishing marginal returns to scale. This argument is drawn from "q-theory," and it provides a risk-based explanation for the accrual anomaly. The investment factor is represented in this paper using the investment-to-asset ratio (*I/A*). Ball et al. (2016) find that accruals predict returns because they are negatively correlated with cash-based operating profitability (*CbOP*) and any increase in profitability as a result of accruals has no impact on the cross-section of returns.

The second group of explanations attributes the anomaly to mispricing. Mispricing would incur arbitrage. However, Shleifer and Vishny (1997) point out that in reality, almost all arbitrage is risky and involves capital cost, which imposes limits on arbitrage and leads to market inefficiency. Mashruwala et al. (2006) further demonstrate that the accrual anomaly partially reflects arbitrage costs, and is concentrated in firms with high idiosyncratic volatility, low prices, and low volumes. These characteristics make it risky for risk-averse arbitrageurs to take a position in such stocks.

Naïve investor fixation (Dechow and Ge, 2006; Richardson et al., 2005; Sloan, 1996; Xie, 2001) is another source of mispricing and a popular explanation for the accrual anomaly. However, the major studies on this explanation focus on the behaviors of investors and firms, and thus they cannot provide proxy variables for the explanations involved (as the decomposition method requires). Therefore, we mainly focus on the explanations based on risk and arbitrage costs.

Prior studies offer several possible explanations for the accrual anomaly from various perspectives. However, no one has ever compared and evaluated these possible explanations, partly due to the methodological difficulties of comparing the contributions of differing factors. On the one hand, traditional empirical methods are not built to quantitatively measure the explanatory power of different explanations. On the other hand, previous studies adopt different methods for constructing variables, both for accruals and explanations, thereby making it difficult to create a unified framework for comparison. To solve these difficulties, we adopt the decomposition method proposed by Hou and Loh (2016). Using stepwise regression, the coefficient on accruals is decomposed into components related to existing explanations and a residual component. As a result, the contribution of each explanation can be quantified and compared with that of other competing explanations in a unified analysis framework.

Based on the empirical results from the decomposition method, we find that *CbOP* (cash-based operating profitability) (Ball et al., 2016) best explains the accrual anomaly, with an explanatory power of about 50% and significance at the 1% level. The value premium (Desai et al., 2004) captures about 22%, and the investment factor (Wu et al., 2010) captures about 16% of the accrual anomaly. In other words, the risk-based explanations, when added together, explain about 90% of the anomaly. As for the explanations based on arbitrage costs (Mashruwala et al., 2006), volume and price explain 20% of the anomaly, whereas idiosyncratic volatility cannot explain the puzzle at all (its explanatory power is less than 0). In addition, the residual unexplained fraction is not statistically different from 0.

These findings show that among risk-based explanations, *CbOP*, a measure that purges accruals from operating profitability, accounts for the biggest part of the accrual anomaly. However, arbitrage costs play a rather limited role. The efficient market theory explains most of the anomaly. Although we do not consider the explanations based on naïve investor fixation, the unexplained residual under the framework in this paper is not statistically different from 0, which indicates that most of the anomaly is explained by the existing explanatory indicators based on risk and arbitrage costs. It is good news to practitioners that the risk-based explanations are adequate to explain the accrual anomaly, as this understanding allows a simple process of adding alternative risk factors into the regressions when predicting future returns, which is more applicable than using naïve investor fixation.

The rest of the paper is organized as follows. Section 2 reviews the current literature on the accrual anomaly. Section 3 presents the methods used to compare the various explanations for the anomaly. Section 4 summarizes the data. Section 5 analyzes the empirical results, and Section 6 draw the conclusion.

2. Literature review

2.1. Accruals

Accruals are an important concept in accounting. According to accrual-based accounting, companies determine the income and expenses of each period in terms of rights and responsibilities. In short, regardless of whether cash is received or paid, all of the income and expenses generated by the current period's business activities should be treated as either income or expenses for the current period.

Accrual-based measurement offers both advantages and disadvantages. Under the assumption of accounting period, accrual-based earnings are determined based on rights and responsibilities, which provides a better measure of performance over the period (Dechow, 1994). However, accrual-based accounting differs from cash-based accounting insofar as companies identify the income and expenses of a period only if the cash is received or paid. Therefore, the income and expenses under the accrual basis of accounting differ from those under the cash basis, because some of the cash receipts can occur in the future or in prior periods. Compared with accrual-based earnings, cash-based profitability is more difficult to manipulate and contains more information about stocks (Ball et al., 2016).

In general, accruals reflect the difference between cash-based profitability and accrual-based earnings (that is, the non-cash receipts and payments). As a result, accounting profit can be divided into two parts: the cash profit (involving cash receipts and payments) and the accruals (the unrealized portion).

2.2. Accrual anomaly

The accrual anomaly was first identified by Sloan (1996), who conducted portfolio analyses that indicated a pattern: the higher the proportion of accruals, the lower the size-adjusted excess returns of a firm's stock. In other words, Sloan demonstrated a significant negative correlation between the proportion of accruals to total assets and the cross-section of size-adjusted abnormal returns. This negative correlation is now known as the "accrual anomaly." Subsequent studies also note that a significant accrual anomaly exists after controlling for firm size (Palmon et al., 2008) and for industry (Lewellen, 2010).

Many asset pricing models have been applied to account for the accrual anomaly, such as the CAPM model, the Fama–French three-factor model, the Carhart four-factor model, the Fama–French five-factor model that includes a profitability factor (Fama and French, 2016), and the q-factor model (Hou et al., 2015). However, none of these models have achieved success in eliminating the anomaly. Using portfolio analysis, Hou et al. (2015) sort stocks into deciles on accruals, and then add an investment factor to the standard factor regressions to analyze the monthly returns. Their findings reveal that alphas in extreme accrual deciles remain significant. Fama and French (2016) adopt a similar method, and examine monthly portfolio returns using the five-factor model with accrual and size factors. Their results show that alphas in extreme groups are still significant.

Other studies show that the accrual anomaly differs from other anomalies. Collins and Hribar (2000) conclude that this anomaly is distinct from post-earnings announcement drift. Barth and Hutton (2004) show that accruals provide incremental information in predicting future returns beyond analysts' forecast revisions.

2.3. Candidate explanations for the accrual anomaly

Any test for the existence of a kind of anomaly is actually a joint test for both the existence of the anomaly and the specification of an asset pricing model. In such tests, it is important to keep in mind that the anomaly (that is, the existence of the alpha benefit after controlling for market risk factors) is not necessarily a true market phenomenon. The anomaly may also appear due to the use of inaccurate market risk factors. Therefore, two points must be considered to explain the existence of a capital market anomaly. First, the model may be misspecified and the fraction of returns which should be explained by market factors is then classified as alpha. In this case, the anomaly is not caused by the market inefficiency. If the model uses the correct asset pricing model, then the anomaly disappears. Second, Although the right market model is adopted, there are several other factors (e.g., market friction, limits to arbitrage, irrational investors) that can lead to market inefficiency. Richardson et al. (2010) also encourage researchers to give primacy to the risk-based explanations rather than those based on market inefficiency.

Currently, the various possible explanations are categorized into two groups: risk-based explanations and mispricing. According to the efficient market hypothesis, the proportion of the excess returns unexplained by market risk factors becomes alpha. The existence of the accrual anomaly is then presumed due to the misspecification of the asset pricing model. Hence, the first group modifies the market model by adding alternative risk factors. Three representative risk-based explanations have been proposed, which focus on the factors of value premium, investment, and *CbOP*.

The first risk factor considered in this paper is the value premium. Desai et al. (2004) suggest that firms with large sales growth (glamour firms) tend to have high positive accruals, whereas firms with small sales growth (value firms) are likely to have negative accruals. As a result, the accrual anomaly is part of the value premium and can be captured by measures related to sales growth. Desai et al. (2004) show that *CFO/P*, a measure of sales growth, explains the accrual anomaly best. However, Cheng and Thomas (2006) reach the opposite conclusion. They demonstrate that *CFO/P* does not eliminate the anomaly, which indicates that the accrual anomaly is distinct from the value-glamour anomaly.

Wu et al. (2010) argue that the investment factor can also capture the anomaly. The q-theory of optimal investment predicts a pattern of diminishing marginal returns to scale (Cochrane, 1991; Hayashi, 1982; Tobin, 1969). Therefore, less profitable investment means lower accruals and higher future returns. Conversely, when more investment projects become profitable, accruals tend to increase, and future returns tend to decrease. A firm's changes in accruals are therefore affected by invested capital. In other words, future returns and accruals are negatively correlated due to a confounder, investment. Based on the Fama–French three-factor model, when the *I/A* (investment-to-asset ratio) is introduced as an additional factor, the accrual anomaly decreases significantly. This interpretation includes an earlier explanation provided by Fairfield et al. (2003), Zhang (2007), and Dechow et al. (2008), namely that of diminishing marginal returns to new investment. However, Momente' et al. (2015) attribute the accrual anomaly to a firm-specific component rather than a related-firm component, which is inconsistent with the standard risk explanation (i.e., that related firms are expected to face similar investment environments and to conduct similar investment behaviors). Therefore, they draw the conclusion that the investment factor's explanatory power is rather limited.

Ball et al. (2016) find that the accrual anomaly becomes more significant after adding the operating profitability, but disappears when replacing the accruals-based profitability variable with *CbOP*, a measure purging accruals from operating profitability. Although it appears that accruals predict returns, this pattern actually occurs due to the negative correlation between the accruals and *CbOP*. Ball et al. (2016) suggest that the motivation for exploring the explanatory power of *CbOP* is similar to the incentive to study the book-to-market ratio in Fama and French (1992). Therefore, we consider *CbOP* as an important risk factor in explaining the accrual anomaly.

Another group of candidate explanations are based on mispricing, or more specifically, arbitrage costs. Several types of market frictions, such as arbitrage risk and arbitrage costs, tend to prevent investors from making risk-free arbitrage. Mashruwala et al. (2006) point out that arbitrageurs cannot eliminate this anomaly via risk-free arbitrage, because the accrual anomaly mainly appears in companies with high idiosyncratic volatility, low volume, and low price. These characteristics usually involve higher arbitrage costs and are difficult to hedge. High arbitrage costs also prevent the elimination of the anomaly via arbitrage. According to Lev and Nissim (2006), the trading positions of investors are not large enough to arbitrage away the accrual anomaly because of the high information and arbitrage costs of implementing a profitable accrual strategy. Moreover, Green et al. (2011) suggest that the apparent demise of the accrual anomaly in recent years is partly due to the increase in capital invested by hedge funds that adopt accruals strategies.

In addition, the original work by Sloan (1996) proposes another kind of mispricing explanation, naïve investor fixation, to explain the accrual anomaly. Sloan argues that investors fail to distinguish between the persistence of the accrual and the cash component of earnings and high-accrual companies are more likely to face an unexpected decline in earnings, leading to a significant negative correlation between accruals and the cross-section of size-adjusted abnormal returns. Consequently, various studies further explore the causes for the differences in persistence between these two components and attribute it to limited attention, earnings management, and accounting distortions (Dechow and Ge, 2006; Hirshleifer et al., 2004; Richardson et al., 2005; Shi and Zhang, 2012; Xie, 2001). However, Kothari et al. (2006) argue that the agency theory of overvalued equity can better explain the accrual anomaly than the naïve investor hypothesis proposed by Sloan (1996).

Using the decomposition method, we analyze the contributions of the explanations mentioned above. As the decomposition method requires building indicators and interpretations based on naïve investor fixation use predictions and tests instead of indicators, we mainly focus on explanations that are based on risk and arbitrage costs. The indicators studied in this paper include cash flows from operations scaled by price (*CFO/P*), investment-to-asset ratio (*I/A*), cash-based operating profitability (*CbOP*), idiosyncratic volatility, volume, and price. The first three indicators (*CFO/P*, *I/A*, and *CbOP*) are risk-based explanatory indicators, and the other three are explanations based on arbitrage costs.

3. Methods

3.1. Fama–MacBeth cross-sectional regression

We start with an existing market model. First, we use the Fama–MacBeth regression to analyze the existence and the magnitude of the accrual anomaly in the US stock market. This method is the quantitative basis of the Fama–French three-factor model (Fama and French, 1992, 1993, 1996), and it offers an important baseline for analyzing the anomaly. In this method, a cross-sectional estimation is made at each time point to obtain the estimated coefficients, and then the arithmetic average of the estimators at all time points is calculated. In the Fama–MacBeth regression, the average coefficient estimates are the monthly returns on the long-short trading strategies, which trade on the portion of the variation in each regressor that is orthogonal to the other regressors. Hence, the *t*-values associated with Fama–MacBeth slopes are proportional to the Sharpe ratios of self-financing strategies.

At each time point, the regression is determined as follows:

$$r_{it} = \alpha_t + \beta_t Acc_{it-1} + \sum_{j=1}^{k} \theta_{jt} x_{ijt} + u_{it} \qquad (1)$$

where r_{it} is the winsorized monthly individual stock return i, Acc_{it-1} is the accruals in the last year, standardized by firm size, and x_{ijt} are control variables. Following previous studies (Ball et al., 2016; Novy-Marx, 2013), we also consider the natural logarithm of the book-to-market ratio lagged by 1 year $(log(B/M))$, the natural logarithm of the firm size lagged by 1 year $(log(Size))$, the prior 1-month return $(r_{1,1})$, and the prior year's return skipping the last month $(r_{12,2})$.

Using this regression, we obtain the average estimated parameter $\hat{\beta}$. We can verify the existence of the accrual anomaly by the sign and significance of $\hat{\beta}$: if $\hat{\beta}$ is significantly negative, then the accrual anomaly exists.

The traditional Fama–MacBeth regression can also be used to analyze whether an explanation D can explain the accrual anomaly. The main idea is as follows: after introducing an explanation D in the regression as one of the control variables, if the coefficient of the accruals is no longer significant, then the explanation theory works. The specific model is as follows:

$$r_{it} = \alpha_t + \beta_t Acc_{it-1} + \sum_{j=1}^{k} \theta_{jt} x_{ijt} + \rho_t D_{it-1} + u_{it} \tag{2}$$

From this regression, we obtain the average estimated parameters $\hat{\rho}$ and $\hat{\beta}$. If the coefficient $\hat{\beta}$ is no longer significant, then the explanation D works and the corresponding explanation theory helps to account for the accrual anomaly.

Although this method is easy and intuitive, it has some disadvantages. First, the results are dichotomous and we cannot quantify the extent of the contribution from the explanation. Indeed, if the coefficient on accruals is still significant after adding the explanatory control variable D, then the precise degree to which this explanation accounts for the anomaly is impossible to determine. Second, this method allows us to test only one explanation at a time, and it does not let us directly compare various explanations in a unified framework.

3.2. The decomposition method by Hou and Loh (2016)

Considering the disadvantages of the traditional Fama–MacBeth regression, we adopt the decomposition method of Hou and Loh (2016), which starts from a two-stage stock-level Fama–MacBeth cross-section regression.

First, we conduct the traditional Fama–MacBeth regression at each month *t* that regresses the stock's *DGTW*-adjusted return on *Acc*:

$$R_{it} = \alpha_t + \beta_t Acc_{it-1} + u_{it} \tag{3}$$

where R_{it} is the stock's *DGTW*-adjusted return computed according to the method proposed by Daniel et al. (1997). This return differs from the winsorized monthly individual stock return *i* adopted in the previous section. Specifically, stocks are first sorted into quintiles based on the firms' sizes in the previous year. Then, stocks are sorted into quintiles based on the previous year's book-to-market ratios within every size quintile. Finally, stocks within each size-*B/M* portfolio are sorted into monthly quintiles based on the prior year's returns skipping the last month. Equal-weighted monthly returns are then computed for each portfolio. The *DGTW*-adjusted return is the raw return minus the return on a size-*B/M*-momentum-matched benchmark portfolio.

Next, we regress Acc on explanation D. The model is as follows:

$$Acc_{it-1} = a_{t-1} + \rho_{t-1} D_{it-1} + \varepsilon_{it-1} \tag{4}$$

The average coefficient $\hat{\rho}$ measures the correlation between the new explanation D and the accruals Acc. Through the linearity property of covariance, we decompose the coefficient on the accruals $\hat{\gamma}$ as obtained in the first step into two parts: γ^C, which is explained by the new explanatory indicator, and γ^R, the unexplained part. Consequently, γ^C/γ is calculated as the percentage of accruals that can be explained by the explanation, and γ^R/γ is the unexplained portion.

$$\gamma^C = \frac{Cov(R_{it}, \rho_{t-1} D_{it-1})}{Var(Acc_{it-1})}, \qquad \gamma^R = \frac{Cov(R_{it}, a_{t-1} + \varepsilon_{it-1})}{Var(Acc_{it-1})} \tag{5}$$

Compared with the Fama–MacBeth regression, the decomposition method offers two main advantages. First, the decomposition method can quantify the contribution that an explanatory indicator makes to explaining the accrual anomaly, and focuses on the indirect impact of each explanation on the returns through accruals (excluding the direct effect). Second, this method allows us to analyze multiple explanations simultaneously. By adding several explanatory indicators in the second step, the contribution of each explanatory indicator is directly compared through the percentages obtained. It is noteworthy that even though the new explanatory indicator D has a strong correlation with accruals, this indicator may still explain a small part of the accrual anomaly, or even may not explain it at all (Hou and Loh, 2016).

4. Data

The sample we analyze includes all companies listed on the NYSE, AMEX, and Nasdaq from December 1996 to November 2016. Following the literature, we delete firm observations that (1) are not common stocks (share codes of 10 or 11), (2) are defined as financial firms with one-digit Standard Industrial Classification (SIC) codes of 6, or (3) have missing values in their explanatory variables. The final sample size is 570,898 observations.

We collect our data from two main resources the Center for Research in Security Prices (CRSP) and Compustat. Monthly market returns with dividends, monthly average prices, and monthly trading volumes are obtained from CRSP, and the annual accounting data are obtained from Compustat. Due to the time lag in the release of annual accounting data, we match firm data from CRSP with those from Compustat, and lag the annual accounting information by one quarter after the end of the fiscal year.

Then, we calculate the main variables by following the construction methods used in previous studies. Appendix B presents details on the construction methods for accruals, cash flows from operations (*CFO*), investment-to-asset ratio (*I/A*), operating profitability (*OP*), and cash-based operating profitability (*CbOP*). In addition, the monthly idiosyncratic volatility is measured as in Mashruwala et al. (2006), as the residual variance from a regression of firm-specific returns on the overall returns of CRSP equally weighted market index during the 48 months before the current month.

Table 1 shows the statistical description for the indicators used in this paper (the original data for *CFO/P* are multiplied by 1,000). Over the sample period, the average monthly stock return is 1.3%, the mean of accruals is 0.9%, the operating profitability is 11.8% on average, and the average cash-based operating profitability is 11%. Our results are similar to those obtained by Ball et al. (2016). Moreover, to prevent extreme values from affecting the results, we apply the Winsor method, replacing the highest and lowest 1% values with the next values counting inwards from the extremes.

5. Empirical results

5.1. Existence of the accrual anomaly: Fama–MacBeth regression

First, we test for the existence of the accrual anomaly in the US stock market using Fama–MacBeth regressions, and the results are shown in Table 2.

Following previous studies (Ball et al., 2016; Novy-Marx, 2013), we consider several control variables, such as the natural logarithm of the lagged book-to-market ratio $(log(B/M))$, the natural logarithm of the lagged market value $(log(M))$, the prior one-month return $(r_{1,1})$ and the prior year's return skipping the last month $(r_{12,2})$. The indicator of interest is the ratio of accruals to total assets (*Acc*).

Our findings, as presented in Table 2, prove the existence of the accrual anomaly during the sample period (the coefficients are multiplied by 100). The first four columns use the complete sample for the regression. In the first column, the coefficient on the ratio of accruals to total assets (*Acc*) is -1.34, with significance at the 1% level. Column (2) controls for industry dummies and shows no significant change compared with Column (1). This second column shows preliminarily evidence for the existence of the accrual anomaly.

Researchers generally agree that the accrual anomaly increases when introducing *OP* into the asset pricing model. Therefore, Columns (3) and (4) in Table 2 add the ratio of *OP* to total assets into regressions. The results reveal that the accrual anomaly increases (from -1.34 to -2.32 without controlling for industry dummies, and from -1.39 to -2.37 after controlling for industry dummies). The *t*-statistics also increase (from -3.62 – -3.83 to -6.23 – -6.45). Hence, the accrual anomaly becomes more significant after adding *OP*, as is consistent with previous studies (Ball et al., 2016; Fama and French, 2015).

The sample analyzed in Columns (5) and (6) excludes small companies (companies in the bottom 20% of the market value). The coefficients on *Acc* in Columns (5) and (6) are still significantly negative, which shows that the accrual anomaly exists in both small and large companies.

5.2. Evaluating candidate explanations: Fama–MacBeth regression

Next, based on the traditional Fama–MacBeth regression, we examine the explanatory power of various candidate explanations for the accrual anomaly in the US stock markets during the sample period.

Table 3 shows the results of the Fama–MacBeth regression to explain the accrual anomaly using the risk-based explanations. In this regression, all of the coefficients on indicators (except for *CFO/P*) are multiplied by 100, and the coefficient on *CFO/P* is divided by 10. The results show that *CbOP* effectively explains and eliminates the accrual anomaly. After adding *CFO/P*, the coefficient on *Acc* also decreases, but it is still significant at the 10% level, indicating that this factor can also explain the anomaly. However, the explanatory power of *I/A* is rather limited.

In Table 3 Column (1), the coefficient on *Acc* is shown to be significantly negative. After introducing *CFO/P* as a risk factor, the absolute values of the coefficients on *Acc* are significantly lower than those in Column (1). In addition, the significance level decreases from 1% to 10%. *I/A* is added in Column (3) and the absolute values of the coefficients on *Acc* decrease, but their magnitudes are lower than values in Column (1). Meanwhile, the absolute values of the *t*-statistics also decrease, but the coefficients on *Acc* remain significant at the 1% level. The results in Column (4) show that the accrual anomaly disappears after introducing *CbOP* as a candidate explanation. The absolute values of the coefficients on *Acc* drop substantially compared with those in Columns (1) and (2), and they are no longer significant.

Table 4 shows the results based on arbitrage costs. According to Mashruwala et al. (2006), the accrual anomaly mainly exists in the sample with high idiosyncratic volatility, low lagged price, and low lagged volume. Therefore, the corresponding dummy variables *DIR*, *DP*, and *DV*, which are constructed using the lowest quintile as the division, are introduced as the explanatory indicators. In each period, *DIR* equals 1 for stocks with the highest (top 20%) idiosyncratic volatility, *DP* equals 1 for stocks with the lowest (bottom 20%) lagged price, and *DV* equals 1 for stocks with the lowest (bottom 20%) lagged volume. In the regression, apart from the dummy for the explanatory indicator itself, we also add the cross-term of the dummy and *Acc*. The results show that after introducing idiosyncratic volatility, the accrual anomaly does not disappear and even becomes more significant. After introducing lagged price and volume, the significance and magnitude of the accrual anomaly decreases to some degree.

In Table 4, Column (1) is the baseline model, and the results are the same as those shown in Column (1) of Table 1. Column (2) introduces the extreme group dummy (*DIR*) and its cross-term with *Acc* (*Acc*×*DIR*) as the explanatory indicators. The results show that the absolute values of the coefficients on *Acc* do not decrease, but increase instead. It is noteworthy that the coefficients on the *DIR* are significantly negative, while the coefficients on *Acc*×*DIR* are positive but not significant. In Column (3), the extreme group dummy for the lagged price (*DP*) and its cross-product with *Acc* (*Acc*×*DP*) are added as the explanatory indicators. The absolute values of the coefficients on *Acc* slightly decrease and the significance also drops. However, the coefficients on *DP* and *Acc*×*DP* are all negative but not significant, indicating that *DP* may not have statistically significant explanatory power and the observed decrease in the coefficients and the significance may be simply due to introducing more dependent variables into the regression. Column (4) explores the explanatory power of volume. The results reveal that the absolute values of the coefficients on *Acc* and the *t*-statistics both decrease slightly. Among the three explanations based on limited to arbitrage, volume appears to have the biggest impact on the accrual anomaly.

5.3. Evaluating candidate explanations: Decomposition method

Based on the Fama–MacBeth regression results presented above, *CbOP* best explains the accrual anomaly. Indeed, *CFO/P*, *I/A*, price, and volume can all partially reduce the accrual anomaly. In addition, idiosyncratic volatility, (one candidate explanation that is based on arbitrage costs) cannot eliminate the anomaly at all. However, due to the limitations of the traditional method, the specific contributions of these indicators cannot be quantified. To this end, in the following section, we study the contributions of all six mechanisms using the decomposition method.

5.3.1. Evaluating the candidate explanations one at a time

In the traditional Fama–MacBeth regressions, we can only measure the explanatory power of the indicators by the difference between their coefficients on accruals before and after introducing the control variables. In fact, these coefficients cannot be compared directly (Hou and Loh, 2016). In order to fix this shortcoming, we further explore the accrual anomaly using decomposition method. First, we analyze the candidate explanations one at a time, which can be seen as a further investigation corresponding to the Fama–MacBeth regressions. In the decomposition method, the cross-product of *DIR* and accruals ($Acc \times D$) contains the *Acc* factor itself. Therefore, *Acc* should be substituted with the decile of *Acc* (*Accd*) to avoid overestimating explanatory power. The results are shown in Table 5 (in which all of the coefficients on indicators except for *CFO/P* are multiplied by 100, and the coefficient on *CFO/P* is divided by 10). Based on these results, *CbOP* is the most powerful indicator for explaining the accrual anomaly.

Table 5 shows that *CbOP* is the largest contributor, as it captures 86% of the accrual anomaly with significance at the 1% level. This indicator is followed by those of price, *CFO/P*, volume, and *I/A*, which have explanatory contributions of 46%, 42%, 24%, and 24%, respectively. In addition, the coefficients on these indicators are significant at the 10% level. In comparison, idiosyncratic volatility can hardly explain the accrual anomaly at all.

In Panel A of Table 5, the significant negative coefficient on *CbOP* in stage two supports the finding by Ball et al. (2016) that accruals predict future excess returns because they are negatively correlated with *CbOP*. Therefore, after introducing *CbOP* into the Fama–MacBeth regressions in Table 3 of Column (4), the significantly negative correlation between excess returns and the accruals disappears. According to the results of *OP* in Columns (3) and (4) of Table 2, we can draw the additional conclusion that the changes in *OP* due to accruals have no impact on the cross-section of returns.

In Panel B of Table 5, the significantly positive coefficients on the interaction effects in stage two reveal that the accrual anomaly is stronger for stocks with high idiosyncratic volatility, low price, and low volume, which is consistent with the findings of Mashruwala et al. (2006). In addition, it is notable that the extreme group dummies for idiosyncratic volatility, price, and volume have negative contributions to the accrual anomaly. The reason for this pattern is that these factors are negatively related to *Acc*, and they negatively predict returns after controlling for *Acc*, according to Table 4. This negative relation works in the opposite direction to that seen in the accrual anomaly. Although the relationships between the extreme group dummies and *Acc* are significant, these indicators do not explain the accrual anomaly. At the same time, the cross-products have slightly higher positive contributions to the anomaly, so that their total explanatory powers are positive.

5.3.2. Evaluating multiple candidate explanations at the same time

Another advantage of the decomposition method is that it can analyze multiple explanatory indicators simultaneously by adding several indicators into the second step of the decomposition. The contribution of each indicator can then be directly compared through the percentages obtained. Therefore, we conduct multivariate analyses in this section.

Table 6 Column (1) shows the decomposition results for the evaluation of all the candidate explanations at the same time. *CbOP* remains the largest contributor. In contrast, among the indicators based on arbitrage costs, only volume makes a significant contribution to explaining the accrual anomaly.

In the first step of the traditional Fama–MacBeth regression, we regress the *DGTW*-adjusted return (raw return minus the return on a size-*B/M*-momentum-matched benchmark portfolio) on *Acc*. Next, we regress the candidate explanations and find that each indicator has a significant effect on accruals. In the third step, the explanatory power of each indicator is calculated separately. The results reveal that the largest contributor is *CbOP*, with an explanatory power of about 52% and significance at the 1% level. This is followed by the indicators of *CFO/P*, *I/A,* price, and volume, which explain 22%, 16%, 14%, and 13% of the anomaly, respectively. The coefficients on these indicators are significant at the 10% level. In contrast, idiosyncratic volatility has almost no explanatory power, capturing only -9.67% of the anomaly, which is not statistically significant. As a result, the residual (i.e., the percentage that cannot be explained by the above six indicators) is statistically insignificant.

Table 6 also shows the results of the decomposition after separately introducing the risk-based and arbitrage costs explanations. We demonstrate that these results do not differ significantly from the results obtained by adding the explanatory indicators together. *CbOP* remains the largest contributor.

Specifically, in Column (2) with only risk-based explanations, no significant change is seen in the explanatory power of *CbOP* (46%, with significance at the 1% level). The explanatory powers of *CFO/P* and *I/A* increase (*CFO/P* from 22% to 40%, and *I/A* from 16% to 27%), and both figures remain significant at the 10% level. These three candidate explanatory indicators based on risk provide the best explanations for the accrual anomaly, with their residuals being not statistically different from 0.

Column (3) introduces only candidate indicators based on arbitrage costs. The explanatory powers of these indicators increase slightly: idiosyncratic volatility increases from -9.67% to 3.31%, price from 14.25% to 21.13%, and volume from 12.63% to 14.19%, with their significance levels remaining unchanged. The total explanatory power of these three indicators is about 44%. In conclusion, these results show that indicators based on the efficient market hypothesis offer the best explanations for the accrual anomaly, with *CbOP* being the largest contributor. The overall contribution of the indicators based on arbitrage costs is comparatively small.

The combined results of the decomposition method and the traditional Fama–MacBeth regression demonstrate that *CbOP* (one of the risk-based explanations) is the largest contributor to explain the accrual anomaly. In contrast, the overall contribution of explanations based on arbitrage costs is rather small.

In summary, the conclusions from decomposition method and Fama-MacBeth regression remain consistent. *CbOP* best explains and eliminates the accrual anomaly. After adding *CFO/P* or *I/A*, both the absolute values and the *t*-statistics of the coefficients on *Acc* decrease, indicating that these two indicators can explain part of the anomaly. Regarding the explanations based on arbitrage costs, price and volume contribute to explaining the accrual anomaly, but idiosyncratic volatility can hardly explain it at all.

6. Conclusions

Using the decomposition method proposed by Hou and Loh (2016), we evaluate several current explanations for the accrual anomaly in the US market between 1996 and 2016. The indicators analyzed in this paper include *CFO/P*, *I/A*, *CbOP*, idiosyncratic volatility, volume, and price. The first three variables are risk-based explanations, and the remaining three variables are explanations about arbitrage costs.

In the decomposition including all indicators, we find that among the three risk-based indicators, *CbOP* is the largest contributor with an explanatory power of about 50% and significant at the 1% level. It is followed by *CFO/P* and *I/A*, which have explanatory powers of about 22% and 16%, with both results being significant at the 10% level. As for explanations based on arbitrage costs, idiosyncratic volatility does not contribute to explaining the anomaly at all. The fraction of the anomaly explained by price and volume are 14% and 13%, respectively. These results are consistent with the Fama–MacBeth regression results.

Overall, the risk-based explanations account for most of the accrual anomaly. In contrast, arbitrage costs explain about 20% of the anomaly, which is a rather limited contribution. Moreover, although naïve investor fixation, a popular explanation for accrual anomaly, is not included in our discussion, the residual is still not statistically different from 0. It indicates that most of the anomaly is explained by risk-based explanations and arbitrage costs. These findings offer good news to practitioners that risk-based explanations are adequate to explain the accrual anomaly. Compared with naïve investor fixation, risk-based explanations are more applicable, as alternative risk factors can be simply added into the asset pricing models when predicting future returns.

Appendix A. Tables

Table 1

Descriptive statistics of the sample

Variable	Mean	Std.	1st	25th	50th	75th	99th
Return	0.013	0.190	-0.408	-0.074	0.001	0.079	0.608
Log(B/M)	-0.741	1.011	-3.506	-1.308	-0.715	-0.144	1.772
Log(M)	5.598	2.107	1.213	4.046	5.579	7.056	10.565
Acc	0.009	0.080	-0.224	-0.018	0.007	0.037	0.237
OP	0.118	0.180	-0.523	0.070	0.133	0.200	0.473
CFO/P	0.110	0.799	-1.107	0.011	0.085	0.173	1.537
I/A	0.035	0.188	-0.438	0.000	0.032	0.082	0.389
CbOP	0.109	0.184	-0.529	0.054	0.124	0.194	0.483
Idiosyncratic volatility	0.148	0.089	0.042	0.091	0.128	0.182	0.470
Price	21.069	32.386	0.380	4.500	12.750	28.010	113.000
Volume	16.504	65.835	0.010	0.507	2.697	10.545	222.879

This table presents the descriptive statistics of the indicators used in this paper (the original data for CFO/P are multiplied by 1,000) from December 1996 to November 2016. The sample is collected from the standard CRSP common stocks (share codes of 10 or 11) listed on the NYSE, Amex, and Nasdaq. We drop financial firms that are defined as firms with a one-digit Standard Industrial Classification (SIC) code of 6, and we exclude companies with missing values in explanatory variables. *Log(B/M)* and *Log(M)* are measured following Ball et al. (2016) and Novy-Marx (2013). Accruals (*ACC*), operating profitability (*OP*), and cash-based operating profitability (*CbOP*) are measured according to Ball et al. (2016). Cash flows from operations scaled by price (*CFO/P*) is the measure of the value premium used by Desai et al. (2004). The investment-to-asset ratio (*I/A*) is a measure of investment used by Wu et al. (2010). Monthly idiosyncratic volatility is measured according to the method in Mashruwala et al. (2006). The results reported in the table are consistent with those obtained by Ball et al. (2016).

Table 2
Existence of the accrual anomaly: Fama–MacBeth regression

Variable	Complete sample		Complete sample		Excluding small companies	
	(1)	(2)	(3)	(4)	(5)	(6)
Acc	-1.34***	-1.39***	-2.32***	-2.37***	-2.03***	-2.07***
	(-3.62)	(-3.83)	(-6.23)	(-6.45)	(-4.49)	(-4.70)
OP	-	-	3.26***	3.29***	1.11***	1.11***
			(8.58)	(8.68)	(2.71)	(2.70)
Log(B/M)	0.39***	0.40***	0.35***	0.35***	0.16*	0.16**
	(4.51)	(5.05)	(4.15)	(4.57)	(1.76)	(1.97)
Log(M)	0.07	0.08	-0.03	-0.03	-0.51***	-0.50***
	(1.27)	(1.43)	(-0.58)	(-0.51)	(-9.09)	(-9.27)
$r_{1,1}$	-2.80***	-3.01***	-2.93***	-3.15***	-1.90***	-2.14***
	(-4.70)	(-5.29)	(-4.97)	(-5.59)	(-3.01)	(-3.57)
$r_{12,2}$	0.47**	0.46**	0.41**	0.39**	0.09	0.07
	(2.45)	(2.49)	(2.18)	(2.16)	(0.39)	(0.32)
Adjusted R^2	3.54%	5.03%	4.01%	5.48%	4.75%	6.71%
Industry	NO	YES	NO	YES	NO	YES

This table presents the results of the traditional Fama–MacBeth cross-sectional regression. The coefficients are multiplied by 100, and the *t*-statistics are reported in parentheses. In the regression, the dependent variable is the winsorized returns, and the common control variables are the natural logarithm of the lagged book-to-market ratio ($log(B/M)$), the natural logarithm of the lagged market value ($log(M)$), the prior 1-month return ($r_{1,1}$), and the prior year's return with the last month skipped ($r_{12,2}$). The indicator of interest is the percentage of accruals on total assets (*Acc*). Columns (1) to (4) use the complete sample, whereas the sample in Columns (5) and (6) excludes small companies (companies in the bottom 20% of the market value). Columns (1), (3), and (5) control for industry dummies. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The results reported in this table confirm the existence of the accrual anomaly. After adding the indicator of operating profitability (OP), the magnitude of the anomaly increases. Columns (5) and (6) prove that the accrual anomaly exists in both small companies and large companies.

Table 3
Fama–MacBeth regression to explain the accrual anomaly (risk-based explanations)

Dependent variable	(1)		(2)		(3)		(4)	
Acc	-1.34***	-1.39***	-0.88*	-0.87*	-1.11***	-1.20***	-0.02	-0.07
	(-3.62)	(-3.83)	(-1.92)	(-1.91)	(-3.05)	(-3.40)	(-0.06)	(-0.19)
Log(B/M)	0.39***	0.40***	0.33***	0.35***	0.38***	0.40***	0.34***	0.35***
	(4.51)	(5.05)	(4.56)	(5.06)	(4.46)	(4.98)	(4.09)	(4.52)
Log(M)	0.07	0.08	0.06	0.06	0.08	0.09	-0.02	-0.01
	(1.27)	(1.43)	(1.04)	(1.17)	(1.44)	(1.57)	(-0.37)	(-0.28)
$r_{1,1}$	-2.80***	-3.01***	-2.87***	-3.09***	-2.82***	-3.03***	-2.92***	-3.14***
	(-4.70)	(-5.29)	(-4.91)	(-5.51)	(-4.77)	(-5.34)	(-4.95)	(-5.57)
$r_{12,2}$	0.47**	0.46**	0.42**	0.40**	0.45**	0.44**	0.42**	0.40**
	(2.45)	(2.49)	(2.27)	(2.26)	(2.35)	(2.40)	(2.24)	(2.22)
CFO/P			0.51**	0.58***				
			(2.42)	(2.84)				
I/A					-0.78**	-0.63**		
					(-2.37)	(-2.25)		
CbOP							3.00***	3.01***
							(8.47)	(8.51)
Adjusted-R^2	3.54%	5.03%	3.90%	5.36%	3.70%	5.14%	3.97%	5.45%
Industry	NO	YES	NO	YES	NO	YES	NO	YES

This table shows the results of the Fama–MacBeth cross-sectional regression for risk-based explanations. All coefficients except those on *CFO/P* are multiplied by 100, and the coefficient on *CFO/P* is divided by 10. The *t*-statistics are reported in parentheses. In the regression, the candidate risk-based explanatory indicators are *CFO/P*, *I/A*, and *CbOP*. Cash flows from operations scaled by price (*CFO/P*) is a measure of the value premium used by Desai et al. (2004). The investment-to-asset ratio (*I/A*) is a measure of investment used by Wu et al. (2010). Cash-based operating profitability (*CbOP*) is measured following Ball et al. (2016). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 4

Fama–MacBeth regression to explain the accrual anomaly (arbitrage costs)

Dependent variable	(1)		(2)		(3)		(4)	
Acc	-1.34***	-1.39***	-1.85***	-1.89***	-1.05**	-1.11**	-0.98**	-1.06**
	(-3.62)	(-3.83)	(-3.95)	(-4.17)	(-2.35)	(-2.55)	(-2.16)	(-2.41)
Log(B/M)	0.39***	0.40***	0.29***	0.31***	0.36***	0.38***	0.38***	0.39***
	(4.51)	(5.05)	(3.79)	(4.33)	(4.34)	(4.89)	(4.55)	(5.10)
Log(M)	0.07	0.08	-0.00	0.01	0.03	0.04	0.06	0.07
	(1.27)	(1.43)	(-0.05)	(0.17)	(0.73)	(0.97)	(0.92)	(1.02)
$r_{1,1}$	-2.80***	-3.01***	-2.92***	-3.14***	-2.98***	-3.19***	-2.83***	-3.04***
	(-4.70)	(-5.29)	(-5.18)	(-5.79)	(-5.19)	(-5.80)	(-5.01)	(-5.61)
$r_{12,2}$	0.47**	0.46**	0.50***	0.49***	0.40**	0.39**	0.48***	0.47***
	(2.45)	(2.49)	(2.71)	(2.71)	(2.21)	(2.23)	(2.67)	(2.71)
DIR			-0.85***	-0.81***				
			(-3.57)	(-3.47)				
Acc×DIR			1.22	1.21				
			(1.49)	(1.49)				
DP					-0.33	-0.32		
					(-1.45)	(-1.40)		
Acc×DP					-1.03	-0.93		
					(-1.33)	(-1.20)		
DV							-0.15	-0.18
							(-0.65)	(-0.76)
Acc×DV							-1.38*	-1.32*
							(-1.69)	(-1.65)
Adjusted-R^2	3.54%	5.03%	4.37%	5.81%	4.12%	5.58%	4.28%	5.74%
Industry	NO	YES	NO	YES	NO	YES	NO	YES

This table shows the results of the Fama–MacBeth cross-sectional regression for explanations based on arbitrage costs. All coefficients are multiplied by 100, and the *t*-statistics are reported in parentheses. In the regression, the candidate explanatory indicators based on arbitrage costs are idiosyncratic volatility, price, and volume. Monthly idiosyncratic volatility is measured according to the method used by Mashruwala et al. (2006). *DIR*, *DP*, and *DV* are constructed using the lowest quintile as the division. In each period, *DIR* equals 1 for stocks with the highest (top 20%) idiosyncratic volatility, *DP* equals 1 for stocks with the lowest (bottom 20%) lagged price, and *DV* equals 1 for stocks with the lowest (bottom 20%) lagged volume. The cross-terms of the dummies and *Acc* are also added into the model. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 5

Decomposing the accrual anomaly: Univariate analysis

Panel A: Risk-based explanations

Stage	Description	Variable	*CFO/P*	*I/A*	*CbOP*
1	DGTW-adj. ret on *Acc*	*Acc*	-1.12***	-1.12***	-1.12***
			(-3.13)	(-3.13)	(-3.13)
2	*Acc* on candidate indicator (*D*)	*D*	-5.73***	10.21***	-7.32***
			(-49.47)	(45.43)	(-46.34)
3	Decompose Stage 1 *Acc* coefficient	*D*	42.10%*	24.36%**	85.94%***
			(1.82)	(2.55)	(2.94)
		Residual	57.90%**	75.64%***	14.06%
			(2.50)	(7.91)	(0.48)

Panel B: Arbitrage costs

Stage	Description	Variable	IR	Price	Volume
1	DGTW-adj. ret on *Acc*	*Acc*	-1.12***	-1.12***	-1.12***
			(-3.13)	(-3.13)	(-3.13)
2	*Acc* on candidate indicator (*D*)	*D*	-13.59***	-13.45***	-11.59***
			(-112.02)	(-110.67)	(-121.71)
		Accd×*D*	2.46***	2.41***	2.07***
			(119.75)	(123.17)	(130.75)
3	Decompose Stage 1 *Acc* coefficient	*D*	-254.06%**	-61.25%	-52.62%
			（-2.29）	(-0.83)	(-0.84)
		Accd×*D*	257.18%**	106.92%	76.63%
			(2.53)	(1.44)	(1.22)
		Total	3.12%	45.66%***	24%*
			(0.15)	(2.89)	(1.90)
		Residual	96.88%***	54.34%***	76%***
			(4.69)	(3.44)	(6.02)

Using the results of the Fama–MacBeth cross-sectional regression, the negative relationship between *Acc* and DGTW-adjusted returns is decomposed into a part that is explained by the new explanatory indicators and a residual component. Stage 1 regresses the *DGTW*-adjusted returns on *Acc* ($R = \alpha + \gamma Acc + u$). Stage 2 regresses *Acc* on one type of candidate explanatory indicator ($Acc = a + \delta D + \mu$). In Stage 3, the γ coefficient from Stage 1 is decomposed into two parts, γ^C, and γ^R. We then calculate γ^C/γ as the measure of the percentage of accruals that can be explained by D, and we calculate γ^R/γ as the measure of the unexplained portion, using the multivariate delta method to calculate the standard errors of each portion. In Stages 1 and 2, all coefficients except those on *CFO/P* are multiplied by 100, and the coefficient on *CFO/P* is divided by 10. Panel A shows the results of risk-based explanatory indicators, whereas Panel B shows the results of indicators based on arbitrage costs. The *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6
Decomposing the accrual anomaly: Multivariate analysis (grouped candidates)

Variable	(1) All the explanations	(2) Risk-based explanations	(3) Arbitrage costs
CFO/P	21.68%*	40.07%*	
	(1.96)	(1.94)	
I/A	16.46%***	26.58%**	
	(2.61)	(2.52)	
CbOP	52.32%***	46.46%***	
	(2.96)	(2.93)	
Idiosyncratic volatility	-9.67%		3.31%
	(-0.60)		(0.26)
DIR	-176.45%**		-168.50%**
	(-2.30)		(-2.29)
Accd×DIR	166.78%**		171.81%**
	(2.52)		(2.52)
Price	14.25%*		21.13%***
	(1.88)		(2.94)
DP	-25.52%		-20.99%
	(-0.77)		(-0.62)
Accd×DP	39.77%		42.12%
	(1.33)		(1.27)
Volume	12.63%*		14.19%*
	(1.88)		(1.86)
DV	-27.59%		-30.17%
	(-0.84)		(-0.80)
Accd×DV	40.22%		44.36%
	(1.19)		(1.17)
Residual	-7.67%	-13.12%	61.37%***
	(-0.31)	(-0.35)	(3.37)

Using the results of the Fama–MacBeth cross-sectional regression, the negative relationship between *Acc* and DGTW-adjusted returns is decomposed into several components, each linked to an explanatory indicator and a residual component for the three groups of explanatory indicators (all the explanations, risk-based explanations, and explanations based on arbitrage costs). All of the coefficients are multiplied by 100, and the *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Appendix B.

Constructing operating profitability, accruals, cash-based operating profitability, operating cash flow, and investment-to-asset ratio

This appendix introduces the methods for constructing the factors of operating profitability, accruals, cash-based operating profitability (*CbOP*), operating cash flow (*CFO*), and investment-to-asset ratio. We adopt the construction methods of previous studies using explanatory indicators.

To calculate operating profitability (*OP*), accruals, and *CbOP*, we adopt the approach proposed by Ball et al. (2016).

1. Operating profitability

OP is calculated based on the income statement:

Operating profitability = Revenue

- Cost of goods sold

- Reported sales, general costs, and administrative expenses

where "Reported sales, general costs, and administrative expenses" are totals after subtracting expenditures on research and development.

2. Accruals

Next, we calculate the absolute value of accruals and of *CbOP* based on the cash flow statement. The reason we do not choose the balance sheet approach is that Hribar and Collins (2002) indicate that accruals obtained from the balance sheet are influenced by firm-level events such as mergers, acquisitions, and etc. Accruals from cash flow statements, however, are not affected by such large events.

Accruals = - Decrease in accounts receivable

- Decrease in inventory

- Increase in accounts payable and accrued liabilities

- Net change in other assets and liabilities

- Increase in accrued income tax

3. Cash-based operating profitability

Cash-based operating profitability = Operating profitability

+ Decrease in accounts receivable

+ Decrease in inventory

+ Increase in accounts payable and accrued liabilities

Finally, we calculate the percentages of the above three indicators in the total assets of the company as measurements of accruals (*Acc*), operating profitability (*OP*), and cash-based operating profitability (*CbOP*), respectively.

4. Operating cash flow

In measuring operating cash flow (*CFO*), we adopt the method used by Desai et al. (2004), by which the *CFO* earnings are adjusted by the depreciation and the accruals:

Operating cash flow = Earnings + Depreciation – Working capital accruals

5. Investment-to-asset ratio

In assessing the investment-to-asset (*I/A*), we follow Wu et al. (2010) and measure *I/A* as follows:

Investment-to-assets = (annual changes in gross property, plant, and equipment + annual changes in inventory) / lagged book value of assets

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