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Keywords: Accruals; Anomalies; Asset pricing; Market efficiency; Limits to arbitrage

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JEL: G12; G14; M41

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1. Introduction

Accruals, an important concept in accounting, reflect the difference between cash-based profitability and accrual-based earnings, that is, 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." However, this correlation is difficult to explain with widely used asset pricing models (Fama and French, 2016; Hou et al., 2015).

Previous studies attempt to explain the anomaly using the efficient market hypothesis (Ball et al., 2016; Desai et al., 2004; Wu et al., 2010) or the market inefficiency theory (Dechow and Ge, 2006; Mashruwala et al., 2006; Sloan, 1996). Nevertheless, no study provides a comprehensive comparison and evaluation of the different possible theories to analyze which one best explains this 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 one that best explains the accrual anomaly. More importantly, by quantifying the contribution of each explanation, we could assess the overall progress of existing current research and provide a reference for future research in the field.

To guide our research, we classify the existing explanations into two groups. The first group is 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 premium. Hence, measures of value premium should be included in the asset pricing model. As a result, we use cash flows from operations scaled by price (*CFO/P*) as the indicator of the value premium. Wu et al. (2010) show that as the discount rate falls, more investment projects become profitable, resulting in higher accruals and lower expected returns. In other words, accruals negatively predict future returns. From this perspective, the accrual anomaly can be considered the result of optimal investment, represented in this paper by 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 that only the cash-based component of operating profitability matters.

The second group of explanations assumes that the market is inefficient and attributes the anomaly to either irrational investors or limits to arbitrage. From the investor irrationality point of view, Sloan (1996) and Dechow and Ge (2006) argue that investors fail to recognize that accruals are less persistent than cash flows, which leads to mispricing. In contrast, from the perspective of limits to arbitrage, Mashruwala et al. (2006) demonstrate that the accrual anomaly is concentrated in firms with high idiosyncratic volatility, making it risky for risk-averse arbitrageurs to take position in stocks. The accrual anomaly also occurs in low-price and low-volume stocks, which indicates that transaction costs prevent investors from exploiting accrual mispricing.

The studies mentioned above 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 methodological difficulties in comparing contributions. 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 indicator constructions and empirical analysis, which makes 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.

After applying the decomposition method, we find that cash-based operating profitability (Ball et al., 2016) best explains the accrual anomaly with an explanatory power of about 50% and significant at the 5% level. The value premium (Desai et al., 2004) and the investment factor (Wu et al., 2010) account for about 15% of the accrual anomaly. In other words, explanations based on alternative risk factors explain 80% of the anomaly. Regarding the limits to arbitrage (Mashruwala et al., 2006) in the market inefficiency group, volume and price explain 20% of the anomaly, whereas idiosyncratic volatility cannot explain the puzzle at all (the explanatory power is less than 0). Meanwhile, the residual unexplained fraction is not statistically different from 0.

These findings show that among current studies based on alternative risk factors, cash-based operating profitability (*CbOP*) accounts for the biggest part of the accrual anomaly, with cash flows from operations scaled by price (*CFO/P*) and investment-to-asset ratio (*I/A*) also contributing to explaining the anomaly. In contrast, limits to arbitrage play a very limited role. In other words, the efficient market theory explains most of the accrual anomaly. Moreover, the fact that the residual is not statistically different from 0 indicates that most of the accrual anomaly is explained by the current explanatory indicators.

The rest of the paper is organized as follows. Section 2 reviews the current literature on the accrual anomaly. Section 3 presents the methods. Section 4 summarizes the data. Section 5 analyzes and discusses the empirical results. Finally, Section 6 concludes the paper.

2. Theoretical background

2.1 Accruals

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

Accrual-based indicators offer both advantages and disadvantages. On the one hand, under the assumption of accounting period, accrual-based earnings are determined based on rights and responsibilities, which provide a better measure of performance over the period (Dechow, 1994). On the other hand, accrual basis accounting differs from cash basis accounting insofar as companies determine the income and expenses of a period only if 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 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 fact, accruals reflect the difference between cash-based profitability and accrual-based earnings, that is, non-cash receipts and payment. As a result, accounting profit can be divided into two parts: cash profit (cash receipts and payment) and accruals (unrealized portion).

2.2 Accrual anomaly

Sloan (1996) first identifies the accrual anomaly. By dividing companies into groups based on the proportion of accruals to total assets, he finds that the larger the proportion of accruals, the lower the size-adjusted excess returns of the company's shares. In other words, he demonstrates the significant negative correlation between the proportion of accruals to total assets and the cross-section of size-adjusted abnormal returns, known as the "accrual anomaly." Moreover, by adopting the strategy of buying stocks with low accrual-asset ratios and selling stocks with high accruals, the average annual rate of excess return was 10.4% between 1962 and 1991. Subsequent studies also note that a significant accrual anomaly exists after controlling for size (Palmon et al., 2008) or industry (Lewellen, 2010).

Many existing asset pricing models have been used to explain the accrual anomaly. However, no model effectively explains it. Between 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), none manages to eliminate the anomaly. Using the portfolio approach, Hou et al. (2015) sort stocks into deciles on accruals and add an investment factor to standard factor regressions to analyze monthly returns. Their findings reveal that intercepts in extreme accrual deciles remain significant. Fama and French (2016) adopt a similar method by examining monthly portfolio returns using the five-factor model with accrual and size factors. Their results show that intercepts in extreme groups are still significant.

Furthermore, Collins and Hribar (2000) conclude that this anomaly is distinct from post-earnings announcement drift. Moreover, using accrual-based profitability as the indicator of profitability, the magnitude of the accrual anomaly increases rather than decreases. It means that the negative correlation between the cross-section of expected returns deepens (Ball et al., 2016; Fama and French, 2015).

2.3 Candidate explanations for the accrual anomaly

Any test of the existence of a kind of anomaly is actually a joint test of the existence of the anomaly and the specification of the asset pricing model. It is important to keep in mind that the anomaly (that is, the existence of the alpha benefit after controlling market risk factors) is not necessarily a true market phenomenon. It may also be due to the use of incorrect market risk factors. Therefore, two points must be considered to explain the existence of a type of capital market anomaly: first, the model is misspecified and the fraction of returns which should be explained by market factors is classified as alpha. In this case, it is not caused by the inefficiency of the market. As a result, by using the correct asset pricing model, the anomaly is explained by the factors and thus disappears. Second, assuming that the right market model is adopted, but there are factors (e.g. market friction, limits to arbitrage, irrational investors), leading to market inefficiency.

Therefore, the accrual anomaly can be explained by the above two ideas. Currently, the possible explanations are categorized into two groups. The first group is based on the efficient market hypothesis and proposes that the pricing model misspecified. Conversely the second group suggests that accruals stem from market inefficiency and that the asset pricing model is correct.

According to the efficient market hypothesis, the proportion of the excess returns unexplained by market risk factors becomes alpha. The existence of accrual anomaly is due to the misspecified asset pricing model. Hence, this kind of explanations modify the market model by adding alternative risk factors. There are three main representative risk factors in this group: value premium, investment, and cash-based operating profitability.

The first risk factor to explain the accrual anomaly is the value premium. Desai et al. (2004) suggest that firms with large sales growth tend to have high positive accruals (glamour firms), whereas firms with small sales growth are likely to have negative accruals (value firms). In other words, discretionary accruals are positively related to forecasted growth. 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 cash flows from operations scaled by price (*CFO/P*), a measure of sales growth, best explains the accrual anomaly. However, Cheng and Thomas (2006) reach the opposite conclusion by demonstrating that *CFO/P* does not eliminate the accrual anomaly. Therefore, they conclude that the accrual anomaly should not be classified as part of the overall value-glamour anomaly.

Wu et al. (2010) argue that the investment factor can also capture the anomaly. Firms optimally adjust their accruals in response to discount rate changes, as predicted by the q-theory of optimal investment (Cochrane, 1991; Hayashi, 1982; Tobin, 1969). A higher discount rate means less profitable investment, lower accruals, and higher future returns. Conversely, when the discount rate falls, more investment projects become profitable, accruals increase, and future returns decrease. In other words, future returns and accruals are negatively correlated. Based on the Fama-French three-factor model, when the investment-to-asset ratio (*I/A*) is introduced as an additional factor, the accrual anomaly decreases significantly. However, Momente' et al. (2015) attribute the accrual anomaly to a firm-specific component rather than a related-firm component, which is not consistent with the standard risk explanation (i.e. related firms are expected to face a similar investment environment and conduct a similar investment behavior). In conclusion, the explanatory power of the investment factor is rather limited.

Ball et al. (2016) contend that cash-based operating profitability (*CbOP*) is an important risk factor to explain the accrual anomaly and argue that accruals, the non-cash component of earnings, represent adjustments made to cash flows to generate a profit measure largely unchanged over time. When the model controls only the profitability factor and not cash-based operating profitability, the accrual anomaly appears. After controlling for *CbOP*, the anomaly decreases significantly.

To summarize, all three explanations mentioned above are based on the misspecification of market model and think that the factors included in the model are not comprehensive. As a result, the introduction of alternative risk factors (cash flows from operations scaled by price, investment-to-asset ratio, cash-based operating profitability) explains the accrual anomaly to a certain extent.

The second group of candidate explanations proposes that the anomaly is caused by market inefficiency. Specifically, it involves two reasons: irrational investors and limits to arbitrage.

On the one hand, some researchers argue that the mispricing of stocks is caused by irrational investors. Sloan (1996) first introduces this point of view. He contends that the persistence of the accrual component of earnings is lower than that of the cash component. However, instead of correctly identifying this difference, investors fail to distinguish the persistence of these two components. As a result, 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.

Dechow and Ge (2006) support the idea that investors misunderstand the different transitory nature of the accrual component and the cash component. They show that earnings persistence is influenced by both the magnitude and the sign of accruals. In high-accrual firms, the persistence of accruals is higher than that of cash flows. In contrast, the persistence of accruals is relatively low in low-accrual firms. It is also lower in low-accrual firms with more special items. However, because investors fail to realize the different persistence of cash and accruals, low-accrual firms with special items earn higher future returns than other low-accrual firms. Shi and Zhang (2012) also find that the more the stock price reacts to earnings and the greater the difference of persistence between cash flows and accruals, the more effective the accrual strategy.

Furthermore, Kothari et al. (2006) argue that the agency theory of overvalued equity can explain the accrual anomaly. They propose that investors overestimate the persistence of accruals only for high-accrual companies, but not for low-accrual deciles, a fact that Dechow and Ge (2006) fail to explain. Indeed, in overvalued companies, CEOs have incentive to keep accruals upwards to remain overvalued. Hence, high-accrual firms tend to be over-represented with overvalued firms. However, this type of unsustainable overvaluation will eventually reverse. In comparison, this phenomenon does not occur in undervalued companies.

On the other hand, other researchers argue that limits to arbitrage may explain the accrual anomaly. Several types of limits, such as arbitrage risk and transaction costs, 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, which is difficult to hedge. In addition, this research reveals that the accrual anomaly appears in stocks with low volume and low price, which usually acquire higher transaction costs. High transaction 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 due to the high information and transaction 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.

Using the decomposition method, we analyze the contribution of the explanations mentioned above. As the decomposition method requires building indicators and interpretations based on irrational investors use predictions and tests instead of indicators, we mainly focus on explanations that based on alternative risk factors and limits to arbitrage. As Table 1 shows, 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*) test explanations based on alternative risk factors, and the other three test the ones based on limits to arbitrage.

3. Methods

3.1 Fama-MacBeth cross-sectional regression

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

At each time point, the regression is as follows:

$$r = \alpha + \gamma Acc + \sum_{j=1}^{k} \theta_j x_j + u \tag{1}$$

Where r is the monthly individual stock return. Acc are accruals in the last year standardized by firm size. x_{ij} 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 estimated parameter $\hat{\gamma}$. We can verify the existence of the accrual anomaly by the sign of $\hat{\gamma}$: if $\hat{\gamma}$ is significantly negative, then the accrual anomaly exists.

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

$$r = \alpha + \gamma Acc + \sum_{j=1}^{k} \theta_j x_j + \rho D + u \tag{2}$$

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

Although this method is easy and intuitive, it has some disadvantages. First, it explores whether the candidate explanation contributes to explaining the accrual anomaly by using the significance of the coefficient on indicator D in the Fama-MacBeth regression. However, the results are dichotomous and cannot quantify the extent of the contribution of this explanation. Indeed, if the coefficient on accruals is still significant after adding the explanatory control variable D, the precise degree of explanation of the indicator D is impossible to determine. Second, we can only test one explanation at a time and cannot directly compare various explanations in a unified framework.

3.2 The decomposition methodology by Hou and Loh (2016)

Considering the disadvantages of the traditional Fama-MacBeth regression, we adopt the decomposition method of Hou and Loh (2016) to test the candidate explanations.

The decomposition method is based on individual stock-level Fama-MacBeth cross-section regressions. First, we conduct the traditional Fama-MacBeth regression for each month *t*:

$$R = \alpha + \gamma Acc + u \quad (3)$$

where R is the stock's DGTW-adjusted return, computed according to Daniel et al. (1997). Specifically, stocks are first sorted into quintiles based on the firms' previous year's size. Then, stocks are sorted into quintiles based on the previous year's book-to-market ratio within every size quintile. Finally, stocks within each size-B/M portfolio are sorted into monthly quintiles based on the prior year's return skipping the last month. Equal-weighted monthly returns are computed for each portfolio. The DGTW-adjusted return is the raw return minus the return on a size-B/M-momentum-matched benchmark portfolio. When $\hat{\gamma}$ is significantly negative, it indicates the existence of the accrual anomaly.

Next, to explore each candidate explanation, we add a new explanatory indicator D in the market model to interpret the accrual anomaly, which means that indicator D should be related to Acc. We then regress Acc, the indicator of accrued profit, on indicator D. The model is as follows:

$$Acc = a + \delta D + \mu \quad (4)$$

The coefficient $\hat{\delta}$ measures the correlation between the new explanatory indicator D and accruals Acc. Moreover, we can use this regression to decompose accruals Acc into two parts orthogonal to each other, δD and $a + \mu$. δD is the part related to the new explanatory indicator D and $a + \mu$ is the part that is not related to D.

Finally, we decompose the coefficient on accruals $\hat{\gamma}$, obtained in the first step, using the linearity property of covariance. The details are the following:

$$\hat{\gamma} = \frac{Cov(R, Acc)}{Var(Acc)}$$

$$= \frac{Cov(R_i, a + \delta D + \mu)}{Var(Acc)} \tag{5}$$

$$= \frac{Cov(R, \delta D)}{Var(Acc)} + \frac{Cov(R, a + \mu)}{Var(Acc)} = \gamma^C + \gamma^R$$

where

$$\gamma^C = \frac{Cov(R, \delta D)}{Var(Acc)}, \qquad \gamma^R = \frac{Cov(R, a + \mu)}{Var(Acc)}$$

In this way, we decompose the coefficient on accruals into two parts: γ^C, which is explained by the new explanatory indicator D_i, and γ^R, the unexplained part. At the same time, we calculate γ^C/γ as the measure of the percentage of accruals that can be explained by D, and γ^R/γ as the measure of the unexplained portion. In addition, Hou and Loh (2016) also obtain the approximation of the mean and variance of the above percentages:

$$E\left(\frac{\gamma^C}{\gamma}\right) \approx \frac{E(\gamma^C)}{E(\gamma)}, \qquad E\left(\frac{\gamma^R}{\gamma}\right) \approx \frac{E(\gamma^R)}{E(\gamma)} \tag{6}$$

$$Var\left(\frac{\gamma^C}{\gamma}\right) \approx \left(\frac{E(\gamma^C)}{E(\gamma)}\right)^2 \times \left(\frac{Var(\gamma^C)}{\left(E(\gamma^C)\right)^2} + \frac{Var(\gamma)}{\left(E(\gamma)\right)^2} - 2\frac{Cov(\gamma, \gamma^C)}{E(\gamma)E(\gamma^C)}\right) \tag{7}$$

$$Var\left(\frac{\gamma^R}{\gamma}\right) \approx \left(\frac{E(\gamma^R)}{E(\gamma)}\right)^2 \times \left(\frac{Var(\gamma^R)}{\left(E(\gamma^R)\right)^2} + \frac{Var(\gamma)}{\left(E(\gamma)\right)^2} - 2\frac{Cov(\gamma, \gamma^R)}{E(\gamma)E(\gamma^R)}\right) \tag{8}$$

The sample estimation is as follows:

$$\hat{E}\left(\frac{\gamma^C}{\gamma}\right) = \frac{\bar{\gamma}^C}{\bar{\gamma}}, \qquad \hat{E}\left(\frac{\gamma^C}{\gamma}\right) = \frac{\bar{\gamma}^R}{\bar{\gamma}} \tag{9}$$

$$\widehat{Var}\left(\frac{\bar{\gamma}^C}{\bar{\gamma}}\right) = \frac{1}{T}\left(\frac{\bar{\gamma}^C}{\bar{\gamma}}\right)^2 \times \left(\frac{s^2_{\gamma^C}}{(\bar{\gamma}^C)^2} + \frac{s^2_{\gamma}}{\bar{\gamma}^2} - 2\frac{\hat{\rho}_{\gamma^C,\gamma} s_{\gamma^C} s_{\gamma}}{\bar{\gamma}\bar{\gamma}^C}\right) \tag{10}$$

$$\widehat{Var}\left(\frac{\bar{\gamma}^R}{\bar{\gamma}}\right) = \frac{1}{T}\left(\frac{\bar{\gamma}^R}{\bar{\gamma}}\right)^2 \times \left(\frac{s^2_{\gamma^R}}{(\bar{\gamma}^R)^2} + \frac{s^2_{\gamma}}{\bar{\gamma}^2} - 2\frac{\hat{\rho}_{\gamma^R,\gamma} s_{\gamma^R} s_{\gamma}}{\bar{\gamma}\bar{\gamma}^R}\right) \tag{11}$$

Compared with the traditional Fama-MacBeth method of regression, the use of the new explanatory theory D as a control variable in the decomposition method offers some advantages.

In the traditional Fama-MacBeth cross-sectional regression, at some point t, the new explanatory indicator D is added as a control variable, and the estimation result is as follows:

$$R = \tilde{\alpha} + \tilde{\gamma}^R Acc + \tilde{\gamma}^C D + \tilde{\varepsilon} \tag{12}$$

If the coefficient $\tilde{\gamma}^R$ in this regression is not significantly different from 0, it suggests that the control variable D explains the accrual anomaly; otherwise, the control variable does not fully explain the anomaly. However, in the traditional regression method, we cannot further measure the degree to which the control variable D explains the accrual anomaly. An intuitive idea is to measure the change of the coefficient on accruals before and after introducing the control variable D_i, that is, the difference between $\tilde{\gamma}^R$ and $\hat{\gamma}$. In fact, the variance terms of the independent variable corresponding to the coefficients $\tilde{\gamma}^R$ and $\hat{\gamma}$ are no longer the same ($\tilde{\gamma}^R$ corresponds to $Var(a + \mu)$, the variance of the part of Acc unrelated to D, while $\hat{\gamma}$ corresponds to $Var(Acc)$, the total variance of Acc). Therefore, these two coefficients cannot be compared directly. In contrast, the decomposition method can compare the coefficients $\hat{\gamma}^C$ and $\hat{\gamma}$ directly (all corresponding to $Var(Acc_i)$, the overall variance of Acc_i). In other words, the decomposition method can quantify the contribution of an explanatory indicator to explain the accrual anomaly.

Moreover, this method can analyze multiple explanatory indicators simultaneously by adding several indicators in the second step. Thus, the contribution of each explanatory indicator is directly compared by the percentages obtained.

It is noteworthy that even though the new explanatory indicator D has a strong correlation with accruals Acc, it may only explain a small part of the accrual anomaly, or even not explain it at all, as shown in Appendix B.

4. Data

First, we collect our sample from the standard CRSP common stock (share codes of 10 or 11) listed on the NYSE, Amex, and Nasdaq and drop financial firms, which are defined as firms with one-digit Standard Industrial Classification (SIC) codes of 6. To be completely comparable, we also exclude companies with missing values in the explanatory variables. In terms of sample period, our sample period starts in December 1996 and ends in November 2016, with 240 months for a total sample size of 345,800.

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 publication of annual accounting data, we match firms from CRSP with those from Compustat and lag the annual accounting information by one quarter after the end of the fiscal year.

Regarding the construction of indicators, we adopt the construction methods used in previous studies. Appendix C presents in detail 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, according to Mashruwala et al. (2006), the monthly idiosyncratic volatility is measured as the residual variance from a regression of firm-specific returns on the returns of CRSP equally weighted market index during the 48 months preceding the current month.

Table 2 shows the statistical description of the indicators used in this paper (the original data for *CFO/P* are multiplied by 1000). Over the sample period, the average monthly stock return is approximately 1.2%, the mean of accruals is about 1%, the operating profitability is 13% on average, and the average cash-based operating profitability is around 12%. Our results are consistent with those obtained by Ball et al. (2016). Moreover, to prevent extreme values from affecting our results, we use the Winsor method, which replaces extreme data exceeding the 1% (99%) quantile with the values at the 1% (99%) quantile.

5. Empirical results

5.1 Existence of the accrual anomaly: Fama-MacBeth regression

First, based on the traditional Fama-MacBeth regression, we test the existence of the accrual anomaly in the US stock market during the sample period.

Table 3 shows the results using the traditional Fama-MacBeth regression. Following previous studies (Ball et al., 2016; Novy-Marx, 2013), we take into account 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 percentage of accruals on total assets (*Acc*).

The estimation results in Table 3 confirm the existence of the accrual anomaly during the sample period (coefficients are multiplied by 100). Columns (1) to (4) use the complete sample for regression. In Column (1), the coefficient on the percentage of accruals on total assets (*Acc*) is -1.24 and the t-statistic is -2.64, which is significant at the 1% level. Column (2) controls for industry dummies and shows no significant change compared with the results in Column (1). It mainly proves the existence of the accrual anomaly. Columns (3) and (4) add the ratio of operating profitability on total assets (*OP*). The results reveal an increase in the absolute values of the coefficients on *Acc* (from -1.24 to -2.16 without controlling for industry dummies, and from -1.30 to -2.23 after controlling for industry dummies). The t-statistics also increase (from -2.64 to -4.66 without controlling for industry dummies, and from -2.81 to -4.81 after controlling for industry dummies). Hence, after adding *OP*, the accrual anomaly persists, and its magnitude increases. This empirical result is consistent with previous studies (Ball et al., 2016; Fama and French, 2015). The sample 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 -1.88 and -1.99, respectively, and are still significantly negative. As a result, we can conclude that the accrual anomaly does not only exist in small companies.

5.2 Evaluating candidate explanations: Fama-MacBeth regression

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

Table 4 shows the results of the Fama-MacBeth regression to explain the accrual anomaly based on the efficient market hypothesis (more specifically, alternative risk factors), in which all coefficients on indicators except *CFO/P* are multiplied by 100 and the coefficient on *CFO/P* is divided by 10. Column (1) is a baseline and does not add any explanatory indicators. Columns (2) to (4) each add one explanatory indicator. The results show that after adding *CbOP*, the significance of the coefficient on *Acc* sharply decreases, showing that *CbOP* effectively explains and eliminates the accrual anomaly. After adding *CFO/P*, the coefficient on *Acc* also decreases (significant at the 10% level), indicating that it can also explain the anomaly. However, the explanatory power of *I/A* is rather limited.

In Table 4 Column (1), the coefficient on *Acc* is significantly negative. Column (2) introduces *CFO/P* as an alternative risk factor, and the absolute values of the coefficients on *Acc* are significantly lower than those in Column (1) (from -1.24 to -0.84 without controlling for industry dummies, and from -1.30 to -0.82 after controlling for industry dummies). In addition, the t-statistics decrease (from -2.64 to -1.58 without controlling for industry dummies, and from -2.81 to -1.54 after controlling for industry dummies), and the coefficients on accruals are no longer significant. *I/A* is added in Column (3) as the alternative risk factor. As a result, the absolute values of the coefficients on *Acc* decrease to a certain degree compared with Column (1) (from -1.24 to -0.98 without controlling for industry dummies, and from -1.30 to -1.11 after controlling for industry dummies). Meanwhile, the absolute values of the t-statistics also decrease (from -2.64 to -2.10 without controlling for industry dummies, and from -2.81 to -2.43 after controlling for industry dummies). However, the coefficients on *Acc* remain significant at the 5% level. Column (4) introduces *CbOP* as a candidate explanation for the accrual anomaly. The results show that the absolute values of the coefficients on *Acc* drop substantially compared with Column (1) (from -1.24 to -0.01 without controlling for industry dummies, and from -1.30 to -0.09 after controlling for industry dummies). In addition, the t-statistics decrease (from -2.64 to -0.02 without controlling for industry dummies, and from -2.81 to -0.18 after controlling for industry dummies), and the coefficients on accruals are no longer significant.

Table 5 shows the results of the Fama-MacBeth regression to explain the accrual anomaly based on market inefficiency (more specifically, limits to arbitrage). According to the limits to arbitrage theory, 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* can be 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. In the regression, apart from the dummy for the explanatory indicator itself, we also add the cross term of the dummy and *Acc*. In Table 5, Column (1) is a baseline and does not include any explanatory indicators. Columns (2) to (4) include one of the candidate explanations based on limits to arbitrage. After introducing the indicator of idiosyncratic volatility, the significance of the coefficient on *Acc* does not change, which shows that the explanatory power of this indicator is quite limited. After introducing the indicators of lagged price and volume, the significance decreases to some degree, indicating that these two indicators have some effect on the explanation and elimination of the anomaly.

In Table 5, Column (1) does not include any candidate explanatory indicators, and the results are the same as those in Column (1) of Table 2. Specifically, the coefficient on *Acc* is significantly negative. Column (2) introduces the extreme group dummy (*DIR*) and its cross term with *Acc* ($Acc \times DIR$) as the explanatory indicators. The results show that the absolute values of the coefficients on *Acc* increase (from -1.24 to -1.34 without controlling for industry dummies, and from -1.30 to -1.45 after controlling for industry dummies). At the same time, the absolute values of the t-statistics decrease but remain larger than in Column (1) (from -2.64 to -2.30 without controlling for industry dummies, and from -2.81 to -2.52 after controlling for industry dummies). In addition, the coefficients on the cross-product of extreme group dummy (*DIR*) and the accrual-to-asset ratio (*Acc*) are positive but not significant. In Column (3), the extreme group dummy for lagged price (*DP*) and its cross product with *Acc* ($Acc \times DP$) are added as the explanatory indicators. The absolute values of the coefficients on *Acc* are slightly lower than those of Column (1) (from -1.24 to -0.94 without controlling for industry dummies, and from -1.30 to -1.02 after controlling for industry dummies). Meanwhile, the absolute values of the t-statistics decrease (from -2.64 to -1.83 without controlling for industry dummies, and from -2.81 to -2.02 after controlling for industry dummies), meaning that the significance drops sharply. The coefficients on the cross-product ($Acc \times DP$) are negative but not significant. Column (4) introduces the extreme group dummy for lagged volume (*DV*) and its cross-product with *Acc* ($Acc \times DV$) as the explanatory indicators. The results reveal that the absolute values of the coefficients on *Acc* are slightly lower than those in Column (1) (from -1.24 to -0.86 without controlling for industry dummies, and from -1.30 to -0.94 after controlling for industry dummies). The t-statistics also decrease slightly (from -2.64 to -1.55 without controlling for industry dummies, and from -2.81 to -1.73 after controlling for industry dummies). Moreover, the coefficients on *Acc*×*DV* are negative but not significant.

5.3 Evaluating candidate explanations: decomposition method

Based on the Fama-MacBeth regression results presented above, cash-based operating profitability (*CbOP*) best explains the accrual anomaly. Indeed, cash flows from operations scaled by price (*CFO/P*), investment-to-asset ratio (*I/A*), price, and volume can partially reduce the accrual anomaly. In addition, idiosyncratic volatility, the candidate explanation based on limits to arbitrage, can hardly eliminate the anomaly. However, due to the limitation of the traditional method, the specific contributions of these indicators cannot be quantified. To this end, in the following section, we study the explanatory powers of these six indicators using the decomposition method.

5.3.1 Evaluating candidate explanations one at a time

First, we analyze the candidate explanations one at a time. Specifically, only one of the explanatory indicators is added to the regression for analysis. According to Hou and Loh (2016), as the cross-product of the extreme group dummy and accruals (*Acc*×*D*) contains the *Acc* factor itself, *Acc* should be substituted with the decile of *Acc* (*Accd*) to avoid overestimating its explanatory power. The results are shown in Table 6 (in which all coefficients on indicators except *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.

Indeed, in Table 6, *CbOP* is the largest contributor; it captures 84% of the accrual anomaly and is significant at the 5% level. It is followed by the indicators of price, volume, *CFO/P*, and *I/A*, with explanatory fractions of 40%, 34%, 32%, 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.

5.3.2 Evaluating multiple candidate explanations at the same time

Table 7 shows the results of the decomposition of the evaluation of multiple candidate explanations at the same time. *CbOP* remains the largest contributor. In contrast, among the indicators based on limits to arbitrage, only volume makes a significant contribution to explaining the accrual anomaly.

In the first step of the traditional Fama-MacBeth regression, we regress DGTW-adjusted return (raw return minus the return on a size-B/M-momentum-matched benchmark portfolio) on *Acc*. The coefficient on *Acc* is -0.98 and significant at the 5% level, which is consistent with our results proving the existence of the accrual anomaly in the previous section. 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 51% and significant at the 5% level. It is followed by the indicators of volume, *CFO/P*, *I/A*, and price, with explanatory fractions of 17%, 16%, 15%, and 11%, respectively. However, the coefficients on these indicators are significant at the 10% level. In contrast, idiosyncratic volatility barely explains the accrual anomaly by capturing only -8.45% of the anomaly. The total explanatory power of the three indicators of alternative risk factors is about 80%. As for the indicators based on limits to arbitrage, the total explanatory power is about 20%. As a result, the residual (i.e., the fraction that cannot be explained by the above six indicators) is close to 0.

Table 8 shows the results of the decomposition after separately introducing the indicators based on alternative risk factors and those based on limits to arbitrage. Our results demonstrate that these decomposition 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 indicators based on alternative risk factors, no significant change is seen in the explanatory power of *CbOP* (still 50% and significant at the 5% level). The contribution of *CFO/P* increases from Column (1) (from 16% to 32.13%). The explanatory power of *I/A* also increases from 15.09% to 25.83% and remains significant at the 10% level. These three candidate explanatory indicators based on alternative risk factors best explain the accrual anomaly, with the residual not statistically different from 0. In Column (3), we only introduce candidate indicators based on limits to arbitrage. The explanatory fractions of these indicators increase slightly: idiosyncratic volatility increases from -8.45% to 0.34%, price from 11.32% to 15.20%, and volume from 17.10% to 20.45%, while their significance levels remain unchanged. Meanwhile, the total explained fraction of these three indicators is less than 40%. In conclusion, the results show that indicators based on the efficient market hypothesis best explain the accrual anomaly, with *CbOP* as the largest contributor. The overall contribution of indicators based on limits to arbitrage is comparatively small.

The combined results of the decomposition method and the traditional Fama-MacBeth regression demonstrate that *CbOP* (indicator based on alternative risk factors) is the largest contributor to explain the accrual anomaly. In contrast, the overall contribution of explanations based on limits to arbitrage (idiosyncratic volatility, price, and volume) is rather small.

The results of the traditional Fama-MacBeth regression show that cash-based operating profitability (*CbOP*) best explains and eliminates the accrual anomaly. After adding *CFO/P* or *I/A*, the absolute values and t-statistics of the coefficients on *Acc* decrease, indicating that these two indicators can explain part of the anomaly. Regarding the explanations based on limits to arbitrage, price and volume contribute to explaining the accrual anomaly, while idiosyncratic volatility can hardly explain it. In summary, the conclusions of these two methods remain consistent.

6. Conclusions

Using the decomposition method proposed by Hou and Loh (2016), we evaluate several current explanations for the accrual anomaly based on the data from the US market between 1996 and 2016. The indicators used 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 variables are based on the efficient market hypothesis (specifically, alternative risk factors), and the remaining three variables are based on the market inefficiency (specifically, limits to arbitrage).

In the regression with all indicators, we find that among the three indicators based on alternative risk factors, cash-based operating profitability (*CbOP*) is the largest contributor with an explanatory power of about 50% and significant at the 5% level. It is followed by the indicators of cash flows from operations scaled by price (*CFO/P*) and investment-to-asset ratio (*I/A*), with explanatory powers of about 15% and significant at the 10% level. As for indicators based on limits to arbitrage, idiosyncratic volatility does not contribute to explaining the anomaly, while price and volume partly explain it. The fractions explained by price and volume are 11% and 17%, respectively. These results are consistent with the Fama-MacBeth regression results.

Overall, explanatory indicators based on alternative risk factors account for about 80% of the accrual anomaly, indicating that most of the anomaly can be explained by explanations based on alternative risk factors. In contrast, indicators based on limits to arbitrage explain less than 20% of the anomaly, a rather limited contribution. This conclusion supports the efficient market hypothesis to explain the accrual anomaly. In addition, the residual unexplained fraction is not statistically different from 0, indicating that the overall progress in the field of the accrual anomaly.

Appendix A. Tables

Table 1

Summary of candidate explanations for the accrual anomaly.

	Explanation	Indicator	Source
Efficient Market (Alternative Risk Factors)	Discretionary accruals are positively related to forecasted growth. Firms with large sales growth are likely to have high positive accruals. As a result, the accrual anomaly should be classified as part of the value premium.	Cash flows from operations scaled by price (*CFO/P*)	Desai, H., Rajgopal, S., Venkatachalam, M., 2004. Value-glamour and accruals mispricing: One anomaly or two? The Accounting Review 79, 355-385.
	A higher discount rate means less profitable investments, lower accruals, and higher future returns. In other words, future returns and accruals are negatively correlated.	Investment-to-asset ratio (*I/A*)	Wu, J., Zhang, L., Zhang, X. F., 2010. The q-theory approach to understanding the accrual anomaly. Journal of Accounting Research 48, 177-223.
	Cash-based operating profitability (*CbOP*) is an important factor. A significant negative correlation exists between *CbOP* and accruals. If the model controls only the profitability factor and not cash-based operating profitability, the accrual anomaly occurs.	Cash-based operating profitability (*CbOP*)	Ball, R., Gerakos, J., Linnainmaa, J. T., Nikolaev, V., 2016. Accruals, cash flows, and operating profitability in the cross section of stock returns. Journal of Financial Economics 121, 28-45.
Inefficient Market (Limits to Arbitrage)	Arbitrageurs cannot reduce the anomaly by risk-free arbitrage because the accrual anomaly mainly occurs in companies with high idiosyncratic volatility, which is difficult to hedge. In addition, research shows that the accrual anomaly appears mainly in stocks with low volume and low price, which usually acquire higher transaction costs. High transaction costs also prevent the elimination of the anomaly through arbitrage.	Idiosyncratic volatility Price Volume	Mashruwala, C., Rajgopal, S., Shevlin, T., 2006. Why is the accrual anomaly not arbitraged away? The role of idiosyncratic risk and transaction costs. Journal of Accounting and Economics 42, 3-33.

Table 2
Descriptive statistics of the sample

Variable	Mean	Std	1st	25th	50th	75th	99th
Return	0.012	0.176	-0.39	-0.067	0.004	0.076	0.559
Log(B/M)	-0.796	0.977	-3.509	-1.34	-0.753	-0.212	1.607
Log(M)	5.954	2.156	1.474	4.381	5.922	7.391	11.236
Acc	0.008	0.077	-0.218	-0.017	0.006	0.033	0.215
OP	0.133	0.169	-0.436	0.08	0.139	0.206	0.506
CFO/P	0.104	0.667	-0.892	0.019	0.086	0.169	1.282
I/A	0.034	0.173	-0.388	0.001	0.03	0.076	0.365
CbOP	0.124	0.173	-0.442	0.067	0.131	0.201	0.519
Idiosyncratic volatility	0.139	0.082	0.038	0.085	0.121	0.173	0.427
Price	24.163	56.989	0.439	5.45	14.71	31.312	120.825
Volume	21.283	80.475	0.016	0.697	3.646	14.04	284.243

Table presents the descriptive statistics of the indicators used in this paper (the original data for CFO/P are multiplied by 1000) from December 1996 to November 2016. The sample is collected from the standard CRSP common stock (share codes of 10 or 11) listed on the NYSE, Amex, and Nasdaq. We drop financial firms, which are defined as firms with one-digit Standard Industrial Classification (SIC) code of 6 and 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 in the table are consistent with those obtained by Ball et al. (2016).

Table 3
Existence of the accrual anomaly: Fama-MacBeth regression

Variable	Complete sample		Complete sample		Exclude small companies	
	(1)	(2)	(3)	(4)	(5)	(6)
Acc	-1.24*** (-2.64)	-1.30*** (-2.81)	-2.16*** (-4.66)	-2.23*** (-4.81)	-1.88*** (-3.34)	-1.99*** (-3.63)
OP	-	-	3.07*** (7.71)	3.03*** (7.57)	2.74*** (6.51)	2.72*** (6.46)
Log(B/M)	0.29*** (3.18)	0.32*** (3.75)	0.30*** (3.28)	0.31*** (3.71)	0.21** (2.14)	0.22*** (2.46)
Log(M)	0.05 (0.97)	0.07 (1.23)	-0.02 (-0.39)	-0.01 (-0.21)	-0.03 (-0.52)	-0.02 (-0.35)
$r_{1,1}$	-2.73*** (-4.33)	-2.94*** (-4.89)	-2.83*** (-4.52)	-3.05*** (-5.12)	-2.38*** (-3.50)	-2.65*** (-4.15)
$r_{12,2}$	0.33 (1.38)	0.31 (1.35)	0.28 (1.21)	0.25 (1.13)	0.23 (0.86)	0.19 (0.74)
Adjusted R^2	3.9%	5.8%	4.4%	6.3%	5.1%	7.4%
Industry	NO	YES	NO	YES	NO	YES

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 skipping the last month ($r_{12,2}$). 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) to (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 table confirms 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 does not exist only in small companies.

Table 4
Fama-MacBeth regression to explain the accrual anomaly based on the efficient market hypothesis (alternative risk factors)

Dependent variable	(1)		(2)		(3)		(4)	
Acc	-1.24*** (-2.64)	-1.30*** (-2.81)	-0.84 (-1.58)	-0.82 (-1.54)	-0.98** (-2.10)	-1.11** (-2.43)	0.01 (0.02)	-0.09 (-0.18)
Log(B/M)	0.29*** (3.18)	0.32*** (3.75)	0.26*** (3.20)	0.28*** (3.69)	0.29*** (3.17)	0.32*** (3.70)	0.29*** (3.16)	0.30*** (3.60)
Log(M)	0.05 (0.97)	0.07 (1.23)	0.04 (0.78)	0.05 (1.00)	0.06 (1.11)	0.07 (1.33)	-0.01 (-0.26)	-0.01 (-0.07)
$r_{1,1}$	-2.73*** (-4.33)	-2.94*** (-4.89)	-2.80*** (-4.50)	-3.01*** (-5.04)	-2.75*** (-4.40)	-2.95*** (-4.93)	-2.83*** (-4.52)	-3.05*** (-5.11)
$r_{12,2}$	0.33 (1.38)	0.31 (1.35)	0.30 (1.28)	0.27 (1.21)	0.31 (1.32)	0.30 (1.32)	0.30 (1.27)	0.27 (1.19)
CFO/P			0.49** (2.02)	0.59** (2.54)				
I/A					-0.87** (-2.03)	-0.62* (-1.66)		
CbOP							2.83*** (7.64)	2.79*** (7.45)
Adjusted-R^2	3.9%	5.8%	4.4%	6.2%	4.2%	6.0%	4.4%	6.2%
Industry	NO	YES	NO	YES	NO	YES	NO	YES

Table shows the results of the Fama-MacBeth cross-sectional regression for explanations based on the efficient market hypothesis (alternative risk factors). All coefficients except 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 explanatory indicators based on the market efficiency hypothesis 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 5
Fama-MacBeth regression to explain the accrual anomaly based on the market inefficiency (limits to arbitrage)

Dependent variable	(1)		(2)		(3)		(4)	
Acc	-1.24*** (-2.64)	-1.30*** (-2.81)	-1.34** (-2.30)	-1.45** (-2.52)	-0.94* (-1.83)	-1.02** (-2.02)	-0.86 (-1.55)	-0.94* (-1.73)
Log(B/M)	0.29*** (3.18)	0.32*** (3.75)	0.20** (2.44)	0.23*** (3.00)	0.27*** (2.96)	0.30*** (3.51)	0.28*** (3.16)	0.31*** (3.70)
Log(M)	0.05 (0.97)	0.07 (1.23)	-0.01 (-0.29)	0.00 (0.02)	0.01 (0.18)	0.02 (0.55)	0.03 (0.53)	0.05 (0.73)
$r_{1,1}$	-2.73*** (-4.33)	-2.94*** (-4.89)	-2.87*** (-4.72)	-3.08*** (-5.30)	-2.90*** (-4.74)	-3.11*** (-5.31)	-2.77*** (-4.61)	-2.97*** (-5.18)
$r_{12,2}$	0.33 (1.38)	0.31 (1.35)	0.34 (1.50)	0.32 (1.47)	0.28 (1.23)	0.26 (1.19)	0.37* (1.66)	0.36 (1.64)
DIR			-0.77*** (-3.42)	-0.75*** (-3.40)				
Acc×DIR			0.29 (0.27)	0.42 (0.41)				
DP					-0.42* (-1.86)	-0.40* (-1.81)		
Acc×DP					-1.19 (-1.21)	-1.06 (-1.09)		
DV							-0.20 (-0.85)	-0.22 (-0.92)
Acc×DV							-1.33 (-1.33)	-1.28 (-1.29)
Adjusted-R2	3.9%	5.8%	4.8%	6.6%	4.6%	6.5%	4.8%	6.6%
Industry	NO	YES	NO	YES	NO	YES	NO	YES

Table shows the results of the Fama-MacBeth cross-sectional regression for explanations based on the market inefficiency (limits to arbitrage). All coefficients are multiplied by 100, and the t-statistics are reported in parentheses. In the regression, the candidate explanatory indicators based on limits to arbitrage 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-term of the dummies and *Acc* are also added in the model. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6

Decomposing the accrual anomaly: Univariate analysis

Panel A: Efficient market

Stage	Description	Variable	*CFO/P*	*I/A*	*CbOP*
1	DGTW-adj ret on *Acc*	*Acc*	-0.98**	-0.98**	-0.98**
			(-2.31)	(-2.31)	(-2.31)
2	Acc on candidate indicator (*D*)	*D*	-6.01***	11.87***	-7.89***
			(-34.32)	(46.02)	(-39.03)
3	Decompose Stage 1 Acc coefficient	*D*	31.64%	23.99%*	83.75%**
			(1.42)	(1.76)	(2.23)
		Residual	68.36%***	76.01%***	16.25%
			(3.07)	(5.56)	(0.43)

Panel B: Inefficient market

Stage	Description	Variable	IR	Price	Volume
1	DGTW-adj ret on *Acc*	*Acc*	-0.98**	-0.98**	-0.98**
			(-2.31)	(-2.31)	(-2.31)
2	Acc on candidate indicator (*D*)	*D*	-12.92***	-12.87***	-11.31***
			(-113.71)	(-109.76)	(-105.37)
		Accd×*D*	2.34***	2.31***	2.02***
			(119.20)	(120.75)	(114.00)
3	Decompose Stage 1 *Acc* coefficient	*D*	-214.22%*	-18.84%	-41.74%
			(-1.73)	(-0.33)	(-0.85)
		Accd×*D*	214.03%*	58.72%	75.74%
			(1.95)	(1.01)	(1.41)
		Total	-0.18%	39.89%*	34.00%*
			(-0.01)	(1.95)	(1.88)
		Residual	100.18%***	60.11%***	66.00%***
			(3.52)	(2.94)	(3.64)

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

Table 7
Decomposing the accrual anomaly: Multivariate analysis

Stage	Description	Variable	Coeff. (Fraction)	
1	DGTW-adj ret on *Acc*	*Acc*	-0.98** (-2.31)	
2	*Acc* on candidate variables	*CFO/P*	-2.77*** (-30.78)	
		I/A	7.47*** (43.46)	
		CbOP	-4.34*** (31.17)	
		DIR	-8.38*** (-74.29)	
		Accd×*DIR*	1.45*** (76.79)	
		DP	-5.73*** (-65.46)	
		Accd×*DP*	1.07*** (74.05)	
		DV	-5.54*** (-79.88)	
		Accd×*DV*	0.92*** (88.39)	
3	Decompose Stage 1 *Acc* coefficient	*CFO/P*	16.00% (1.54)	
		I/A	15.09%* (1.75)	
		CbOP	50.97%** (2.25)	
		DIR	-147.12%* (-1.73)	Sum of IR -8.45% (-0.41)
		Accd×*DIR*	138.67%* (1.92)	
		DP	-8.53% (-0.35)	Sum of Price 11.32% (1.21)
		Accd×*DP*	19.84% (0.84)	
		DV	-25.54% (-0.95)	Sum of Volume 17.10%* (1.81)
		Accd×*DV*	42.63% (1.43)	
		Residual	-2.02%	

	(-0.07)

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 using the decomposition method. In Stages 1 and 2, all coefficients except on *CFO/P* are multiplied by 100, and the coefficient on *CFO/P* is divided by 10. Candidate explanations include indicators based on alternative risk factors (*CFO/P*, *I/A*, and *CbOP*) and indicators based on limits to arbitrage (idiosyncratic volatility, price, and volume). The t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 8
Decomposing the accrual anomaly: Multivariate analysis (grouped candidates)

Variable	(1) All indicators	(2) Indicators based on the efficient market hypothesis	(3) Indicators based on the market inefficiency
CFO/P	16.00%	32.13%	
	(1.54)	(1.59)	
I/A	15.09%*	25.83%*	
	(1.75)	(1.78)	
CbOP	50.97%**	51.92%**	
	(2.25)	(2.21)	
Idiosyncratic volatility	-8.45%		0.34%
	(-0.41)		(0.02)
DIR	-147.12%*		-141.42%*
	(-1.73)		(-1.71)
Accd×DIR	138.67%*		141.76%*
	(1.92)		(1.90)
price	11.32%		15.20%
	(1.21)		(1.58)
DP	-8.53%		-7.96%
	(-0.35)		(-0.31)
Accd×DP	19.84%		23.16%
	(0.84)		(0.88)
volume	17.10%*		20.45%*
	(1.81)		(1.88)
DV	-25.54%		-27.02%
	(-0.95)		(-0.88)
Accd×DV	42.63%		47.47%
	(1.43)		(1.41)
Residual	-2.02%	-9.88%	64.01%**
	(-0.07)	(-0.22)	(2.59)

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 indicators, indicators based on alternative risk factors, and indicators based on limits to arbitrage). All 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.

This appendix demonstrates that although the new explanatory indicator D has a strong correlation with accruals Acc, it may only explain a small part of the accrual anomaly, or even not explain it at all. We add the regression of Acc_i in the traditional Fama-MacBeth cross-sectional regression as follows:

$$\begin{aligned} R &= \tilde{\alpha} + \tilde{\gamma}^R Acc + \tilde{\gamma}^C D + \tilde{\varepsilon} \\ &= \tilde{\alpha} + \tilde{\gamma}^R (a + \delta D + \mu) + \tilde{\gamma}^C D + \tilde{\varepsilon} \\ &= \tilde{\alpha} + \tilde{\gamma}^R (a + \mu) + (\tilde{\gamma}^C + \delta\tilde{\gamma}^R) D + \tilde{\varepsilon} \\ &= \tilde{\alpha} + \tilde{\gamma}^R (a + \mu) + \breve{\gamma}^C D + \tilde{\varepsilon} \end{aligned}$$

where $\breve{\gamma}^C = \tilde{\gamma}^C + \delta\tilde{\gamma}^R$. As a result, we can get the expression of γ^C:

$$\begin{aligned} \gamma^C &= \frac{Cov(R, \delta D)}{Var(Acc)} \\ &= \frac{Cov(R, \delta D)}{Var(\delta D)} \cdot \frac{Var(\delta D)}{Var(Acc)} \\ &= \frac{\breve{\gamma}^C}{\delta} \cdot \frac{Var(\delta D)}{Var(Acc)} \\ &= \left(\frac{\tilde{\gamma}^C}{\delta} + \tilde{\gamma}^R\right) \cdot \frac{Var(\delta D)}{Var(Acc)} \end{aligned}$$

As shown in the above formula, the absolute value of γ^C not only depends on $\frac{Var(\delta D)}{Var(Acc)}$, the contribution of the new explanatory indicator D to explain accruals Acc, but also on $\tilde{\gamma}^C$, the ability of the part unrelated to accruals to explain the excess return R. Although the explanatory indicator D has a strong correlation with accruals Acc, if the part of D that is unrelated to accruals can barely explain the excess return R, then the contribution percentage of the new explanatory indicator will be small or even negative.

Appendix C.

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

This appendix introduces the construction methods of operating profitability, accruals, cash-based operating profitability, operating cash flow, and investment-to-asset. We adopt the construction methods of previous studies using explanatory indicators.

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

Operating profitability

The operating profitability is calculated based on the income statement:

Operating profitability = Revenue
- Cost of goods sold
- Reported sales, general, and administrative expenses

where "Reported sales, general, and administrative expenses" subtracts off expenditures on research and development.

Accruals

Next, we calculate the absolute value of accruals and cash-based operating profitability based on the cash flow statement:

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

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 indicators of accruals (*Acc*), operating profitability (*OP*), and cash-based operating profitability (*CbOP*), respectively.

Operating cash flow

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

Operating cash flow = Earnings + Depreciation – Working capital accruals

Investment-to-asset ratio

In terms of 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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