International Journal of Economics and Financial Research
ISSN(e): 2411-9407, ISSN(p): 2413-8533
Vol. 8, Issue. 3, pp: 78-84, 2022
URL: https://arpgweb.com/journal/journal/5
DOI: https://doi.org/10.32861/ijefr.83.78.84

Academic Research Publishing Group

Original Research **Open Access**

The Pricing of Discretionary Accruals Revisited: The Application of Mixtures of Regressions Based on Asymmetric Investor Behavior

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Article History
Received: 22 March, 2022
Revised: 5 June, 2022
Accepted: 3 July, 2022
Published: 9 July, 2022

Abstract

This paper reexamines the issue of the pricing of discretionary accruals using the approach of mixtures of regressions. In contrast to previously documented contemporaneous results, this study retests the issue by addressing the heterogeneous perceptions and behaviors of investors when they encounter various conditions of return and risk. The empirical results of this study indicate that market investors positively value discretionary accruals when the stock they invest in experiences a rise in price and carries a low degree of risk. Conversely, investors negatively value managerial accruals for stock that shows a fall in price and carries a high degree of risk.

Keywords: Discretionary accruals; Stock returns; Mixtures of regressions; Behavioral finance.

1. Introduction

Research on accounting accruals is prevalent see Larson *et al.* (2018). Firms may use accounting accruals as a tool to communicate their financial potential to interested parties (i.e., efficient earnings management). However, others assert that managers can behave opportunistically by taking advantage of accounting accruals to maximize their utilities (i.e., opportunistic earnings management). Therefore, it is not surprising that the empirical evidence on the pricing of discretionary accruals is inconclusive (i.e., evidence of the positive pricing include (Barth *et al.*, 1999; Kasznik and Mcnichols, 2002; Myers *et al.*, 2007; Subramanyam, 1996; Trueman and Titman, 1988); conversely, evidence of the negative pricing is found in (Abbas *et al.*, 2006; Fernandes and Ferreira, 2007; Salehi *et al.*, 2018; Wu *et al.*, 2014; Zhang *et al.*, 2006).

To test the issue, we address a potential non-uniform relation between accounting accruals and subsequent stock returns using the approach of mixtures of regressions (or the switching regression model), which was introduced by Quandt (1958). The switching regression model has been successfully applied to various disciplines, including astronomy, biology, economics, engineering, and finance (see Wirjanto and Xu (2009) for a survey). This study serves as the first attempt to apply the switching regression model to test the non-monotonic relation between accounting accruals and subsequent stock returns.

To measure the degree of accounting accruals, the independent variable, we use the amount of absolute value of discretionary accruals (referred to as $|DA|$ hereafter) as the proxy. Like those documented in the literature, increasing $|DA|$ implies there is a higher degree of earnings management, and vice versa. To test whether investors positively or negatively value $|DA|$, the dependent variable in the regression analysis is the subsequent quarterly stock returns (referred to as *RET* hereafter). To derive subsequent stock returns, we compute quarterly stock returns of the studied stocks after the closing of the fiscal year. For the purpose of data analysis, we obtain 31,469 firm–year observations from 5,678 nonfinancial companies between 1996 and 2015. The empirical evidence obtained from our analyses demonstrates that the relation between $|DA|$ and *RET* is not uniform across the various conditions of return and risk. In particular, there is a positive relation between $|DA|$ and *RET* for stocks with a positive return mean and a low level of risk. On the other hand, there is a negative relation between $|DA|$ and *RET* for stocks with a negative return mean and a high degree of risk. Our results provide the evidence to support the literature on behavioral heterogeneity in stock market and help to reconcile the mixed results in the literature concerning the pricing of accounting accruals.

The rest of the paper is organized as follows. Section 2 reviews the literature and develops research inquiries. Section 3 describes the measurement of the variables. Section 4 presents the model specifications and discusses why the switching regression model is an appropriate method for our study. Section 5 shows and discusses the empirical results. Finally, Section 6 concludes the investigation.

2. Literature Review and Research Development

2.1. Studies on Earnings Management Pricing

Whether stock markets positively or negatively price discretionary accruals has been documented in the literature. Nevertheless, the evidence reported in the literature is inconclusive, as some find that stock markets positively price managerial discretion in accruals (e.g., Jiraporn *et al.* (2008); Myers *et al.* (2007) Kasznik and Mcnichols (2002), while others show otherwise (e.g., Zhang *et al.* (2006); Fernandes and Ferreira (2007) Wu *et al.* (2014); Salehi *et al.* (2018). The positive relation is based on the argument that investors choose to associate with firms engaging in income smoothing because this activity could lead to stock price appreciation. On the other hand, if market participants perceive discretionary accruals as earnings manipulation, they will negatively value discretionary accruals.

2.2. Research Development

Given ongoing debates on the issue, this study examines the role of investor perceptions and behavior in the pricing of managerial accruals. We address the question of whether stock investors value accounting accruals differentially when encountering gain versus loss as well as high versus low degree of risk. Our argument is closely related to other work in behavioral finance, a new and fast-growing area (see Hirshleifer (2001); Barberis and Thaler (2003) for a survey). For instance, the prospect theory developed by Kahneman and Tversky (1979) implies that investors behave differently when encountering gains versus losses. Based on the asymmetric behaviors of investors, we hypothesize that the conditions of gain versus loss and high versus low risk may influence investors' perceptions on accounting accruals by corporate managers and thus affect whether they positively reward or negatively punish accounting accruals.

3. Measurement of Variables

3.1. Discretionary Accruals

We employ the modified Jones (1991) model proposed by Kothari *et al.* (2005) to calculate discretionary accruals:

$$\frac{TA_{i,t}}{A_{i,t-1}} = \beta_{1,t}\frac{1}{A_{i,t-1}} + \beta_{2,t}\frac{\Delta SALE_{i,t} - \Delta REC_{i,t}}{A_{i,t-1}} + \beta_{3,t}\frac{PPE_{i,t}}{A_{i,t-1}} + \beta_{4,t}ROA_{i,t-1} + \mu_{i,t} \qquad (1)$$

where, for firm *i* and year *t*, *TA* represents total accruals (i.e., Net Income – Operating Cash Flows); *A* stands for the value of total assets; $\Delta SALE$ is the change in net sales; ΔREC denotes the change in net accounts receivable; *PPE* is gross property, plant, and equipment; and *ROA* is the rate of return on assets. The residual term (i.e., $\mu_{i,t}$) from Equation (1) represents the unexplained part of *TA*. Prior studies denote the residuals as discretionary accruals (*DA* hereafter). Following Hribar and Nichols (2007) and many others, we use the $|DA|$, the absolute value of discretionary accruals, to measure the degree of earnings management by corporate managers. It should be noted that Equation (1) is estimated by year–industry, using two-digit Standard Industrial Classification (SIC) codes and at least ten observations, as suggested by Klein (2002).

3.2. Subsequent Stock Returns

The dependent variable in our regression is quarterly stock returns following the year in which discretionary accruals are measured. We regress subsequent quarterly stock returns on $|DA|$ to assess the pricing of accounting accruals.

4. Model Specifications

4.1. The No-Switching Model

To test the issue of the pricing of $|DA|$, the conventional linear model is specified as follows:

$$RET_{i,t+1q} = \alpha + \beta \times |DA|_{i,t} + e_{i,t},\ e_{i,t} \sim N(0, \sigma) \qquad (2)$$

The explained variable $RET_{i,t+1q}$ is the subsequent quarterly stock return and thus the β parameter measures the pricing of $|DA|$. The no-switching model in equation (2) is potentially limited due to the use of a constant measure for the pricing of $|DA|$. That is, the β parameter is fixed for the whole sample population.

4.2. The Switching Regression Model

To capture asymmetric behavior and perceptions of investors under different conditions of return and risk, we develop a switching regression system as follows:

$$RET_{i,t+1q} = \alpha_1 + \beta_1 \times |DA|_{i,t} + e_{1,it} \ \textit{where}\ e_{1,it} \sim N(0, \sigma_1)\ \textit{if}\ s_{i,t} = 1$$
$$RET_{i,t+1q} = \alpha_2 + \beta_2 \times |DA|_{i,t} + e_{2,it} \ \textit{where}\ e_{2,it} \sim N(0, \sigma_2),\ \textit{if}\ s_{i,t} = 2 \qquad (3)$$

Notably, $s_{i,t}$ is a state variable and a two-state system is defined in Equation (3): regime I (namely, $s_{i,t} = 1$) is set where the pricing of $|DA|$ is measured as β_1 under the condition of return mean = α_1 and return volatility = σ_1, while regime II (namely, $s_{i,t} = 2$) is set where the pricing of $|DA|$ is measured as β_2 under the condition of return mean = α_2 and return volatility = σ_2. Next, we use the logistic function to define the probability of each state:

$$prob\,(s_{i,t} = 1) = exp\,(\theta)/[1 + exp\,(\theta)]$$
$$prob\,(s_{i,t} = 2) = 1 - prob\,(s_{i,t} = 1) \qquad (4)$$

Comparing Equation (3) with (2) reveals that the latter is a special case of the former with the restriction of $\beta_1 = \beta_2$, $\alpha_1 = \alpha_2$ and $\sigma_1 = \sigma_2$. Moreover, Equation (3) is flexible to accommodate the potential non-uniform pricing of $|DA|$ under various conditions of return mean and volatility.

The switching regression model developed in this study is related to Engel and Hamilton (1990), Engel (1994) and other related studies in the following respects. First, whereas Engel and Hamilton (1990) define a regime-switching setting with two states on the intercept term (i.e., α_1 and α_2) and standard deviation (i.e., σ_1 and σ_2.) of regression equation for exchanger rate returns, this study focuses on the two states on the slop term (i.e., β_1 and β_2). Our ideas are presented as follows. Examining the realized values of stock returns clearly reveals that some stocks are associated with a negative return and/or carry a high risk, a derivative question is: what is the relationship between the pricing of accounting accruals and the condition of stock return and risk? Specifically, would investors still positively reward $|DA|$ for stocks with a negative return and high risk?

To examine the non-uniform relationship between $|DA|$ and stock return, one might think of a two-step estimation procedure. The typical procedure is that in the first step, some subjective criteria are applied to divide sample stocks into various subsets. In the second step, the traditional estimation methods, such as OLS, are used to describe the relationship and to conduct comparative analyses between the partitioned segments. This two-step analysis implicitly assumes that the partitioning process is exogenous. To the extent that the relation between $|DA|$ and stock return is conditional on the mean and risk of the latter, the switching regression model analyzes the sample segmentation and the relation jointly and endogenously based on the data. We use a one-step approach to estimate the model parameters using the maximum likelihood estimation method, detailed in the Appendix.

5. Empirical Results

5.1. Data and Descriptive Statistics

Our sample includes non-financial U.S. firms with all the required data from 1996 to 2015. We collect the data from the Compustat and CRSP databases. The overall sample consists of 5,678 firms and 31,469 firm-year observations. Table 1 contains detailed variable definitions and the descriptive statistics for these variables.

5.2. Estimation Results of the No-Switching Model

Table 2 presents the result of the no-switching model. First, the correlation between $|DA|$ and *RET* is 0.0187 (p-value < 0.001), as shown in Table 1. Next, as shown in Table 2, the estimated coefficient on $|DA|$ (i.e., β) is 0.0143 (p-value <0.001). These results provide evidence of positive pricing of $|DA|$, as consistent with the mainstream literature on the issue. We argue that these analyses do not address the potential non-uniform behaviors of investors under various conditions of return and risk. We address this issue using the switching regression model.

5.3. Estimation Results of the Switching Regression Model

Table 3 presents the estimation results of the switching regression model. The model sorts stocks into two groups (or regimes) based on their return mean and volatility. First, the percentage for Regime I is 61.79%, and it is higher than that for Regime II (38.21%). The result implies that Regime II includes a relatively small proportion of the sample. Second, for Regime I, the estimated coefficient on $|DA|$ is significantly positive (β_1 = 0.0333 with p-value < 0.001). However, the estimated coefficient on $|DA|$ becomes significantly negative in Regime II (β_2 = -0.0087 with p-value = 0.0687). These results show evidence of switching relations (i.e., from positive to negative) between $|DA|$ and *RET* across various regimes and the positive and negative relation occurs in Regime I and II, respectively.

Last but not least, Tables 2 and 3 report the value of the log-likelihood function, the Akaike information criterion (AIC), and the Schwarz value, three common model selection statistics. Importantly, the switching regression model has a higher value of the log-likelihood function, AIC, and Schwarz value in comparison with the no-switching model. This result indicates that the switching regression model is a more effective model in matching dynamics of stock returns when compared to the no-switching model. Further, as shown in Table 3, the null hypothesis of $\beta_1 = \beta_2$, single pricing of $|DA|$, is rejected at a 1% level of significance. This result provides evidence to support non-uniform pricings of $|DA|$, proposed in this study.

5.4. Implications and Discussion

This finding requires further explanations. First, prior studies on the issue of pricing of $|DA|$ invariably show a positive relation between $|DA|$ and *RET*. However, these studies do not consider behavioral heterogeneity in investors when they encounter various conditions of return and risk. In this study, we argue that the pricing of $|DA|$ is contingent upon the level of return and risk. In particular, we highlight two remarkable financial behaviors: stop-loss limit and risk aversion. We postulate that stock investors could become defensive and be more concerned about the quality of financial reports when the stocks in which they have invested are associated with a negative return and a high risk. In these scenarios, investors would consider accounting accruals (i.e., $|DA|$) as an opportunistic earnings management strategy that allows managers to take advantage of discretions in accounting principles for personal gain. Investors would penalize earnings manipulation behavior and thus negatively price $|DA|$. On the other hand, when investors enjoy a positive return and a low level of risk with the stocks they have invested in, they would probably act aggressively and have less concern about the quality of financial statements. Under this condition, investors perceive accounting accruals as a tool for corporate managers to communicate their financial potential to markets (i.e., efficient earnings management) and thus positively reward earnings smoothing behaviors.

Returning to Table 3, the results of our switching regression model show that the estimate of α_1 is significantly positive (coeff. = 0.0359 with p-value < 0.001) and the estimate of α_2 is significantly negative (coeff. = -0.0519 with p-value < 0.001). Moreover, the estimate of σ_1 (0.1332) is significantly lower than σ_2 (0.2874). Thus, we may define Regime I as the regime with a positive return mean and a low risk and Regime II as the regime with a negative return mean and high risk. Moreover, under Regime I, the positive pricing of $|DA|$ (β_1 = 0.0333), as demonstrated by prior studies, is observed. However, in Regime II, the pricing of $|DA|$ becomes negative (β_2 = -0.0087).

We summarize our findings as follows. First, consistent with prior studies, we find evidence of positive pricing of $|DA|$ in the majority of observations of our sample (i.e., 61.79%). Second, we further find evidence that $|DA|$ would be negatively priced for stocks with a negative return and a high risk. Our results echo the literature on heterogeneous agent models in which investors are assumed to have heterogeneous expectations under certain conditions (see Hommes (2006) for a survey). Further, we compare the results obtained with the switching regression model (i.e., β_1 = 0.0333 versus β_2 = -0.0087 in Table 3) with the no-switching model (i.e., β = 0.0143 in Table 2). The comparison indicates that employing the no-switching model, in which data are pooled together without considering the asymmetries from various regimes of return mean and risk, underestimates the magnitude of positive pricing of $|DA|$ in the positive-return and low-risk regime and leads to the wrong conclusion with regard to the pricing of $|DA|$ in the negative-return and high-risk regime.

6. Conclusions

Whether investors positively or negatively value accounting accruals has been a longstanding debate in the research field. This study represents one of the first studies to employ the approach of mixtures of regressions to analyze the non-uniform relation between accounting accruals and subsequent stock returns across various conditions of return and risk. Our data is a sample of U.S. non-financial firms over the period 1996-2015.

Our empirical results show positive pricing of accounting accruals in the majority of our sample, as consistent with the findings of most prior studies. However, the pricing of accounting accruals becomes negative for stocks with a negative return and a high degree of risk. Further, the longstanding puzzle for the pricing of accounting accruals among earlier studies is satisfactorily accounted for by our empirical findings.

Appendix

Maximum Likelihood Estimation

To estimate the model, we want to find the set of parameters that maximize the likelihood function. As shown in Equation (3), the two-state system is defined as:

$$RET_{i,t+1q} = \alpha_1 + \beta_1 \times |DA|_{i,t} + e_{1,it} \text{ where } e_{1,it} \sim N(0, \sigma_1) \text{ if } s_{i,t} = 1$$

$$RET_{i,t+1q} = \alpha_2 + \beta_2 \times |DA|_{i,t} + e_{2,it} \text{ where } e_{2,it} \sim N(0, \sigma_2) \text{, if } s_{i,t} = 2$$

Given the Gaussian specification for the error term, the corresponding *PDF* (probability density function) for each state is:

$$PDF\,(s_{i,t} = 1) = \frac{1}{\sqrt{2\pi}\sigma_1} exp\left\{\frac{-[RET_{i,t+1q} - (\alpha_1 + \beta_1 \times |DA|_{i,t})]^2}{2 \times \sigma_1^2}\right\}$$

$$PDF\,(s_{i,t} = 2) = \frac{1}{\sqrt{2\pi}\sigma_2} exp\left\{\frac{-[RET_{i,t+1q} - (\alpha_2 + \beta_2 \times |DA|_{i,t})]^2}{2 \times \sigma_2^2}\right\}$$

In this study, we use the logistic function to define the probability of each state:

$$prob\,(s_{i,t} = 1) = exp\,(\theta)/[1 + exp\,(\theta)]$$

$$prob\,(s_{i,t} = 2) = 1 - prob\,(s_{i,t} = 1)$$

We then multiply the *PDF* for each state by the corresponding probability of state to yield the weighted *PDF* as the likelihood function for firm *i* at time *t*:

$$l_{i,t} = prob\,(s_{i,t} = 1) \times PDF\,(s_{i,t} = 1) + prob\,(s_{i,t} = 2) \times PDF\,(s_{i,t} = 2)$$

We create a log-likelihood function Ψ that is the sum of the natural logarithm of the likelihood function for all firms and times:

$$\Psi = \sum_{i=1}^{N}\sum_{t=1}^{T} \ln[\,l_{i,t}(RET_{i,t+1q}, |DA|_{i,t}; \alpha_1, \alpha_2, \beta_1, \beta_2, \sigma_1, \sigma_2, \theta)]$$

Finally, we use OPTIMUM, a software package from GAUSS, and the built-in Broyden–Fletcher–Goldfarb–Shanno algebra to search for the model parameters, including α_1, α_2, β_1, β_2, σ_1, σ_2, θ, that maximizes the above log-likelihood function.[1]

[1] The structural and statistical properties of the OPTIMUM function are well documented in the GAUSS handbook. This study thus omits the statistical properties of the model estimation.

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Table-1. Basic statistics and definition of variables

Panel A: Descriptive statistics of variables

Variable	Mean	Standard Dev.	Median	Q1	Q3
RET	0.0050	0.2114	0.0189	-0.1008	0.1308
|DA|	0.1560	0.2114	0.0629	0.0256	0.1510

Panel B: Correlation matrix

	RET	*|DA|*
RET	1.0000	
|DA|	0.0187	1.0000

Variable definitions:

RET	=	Subsequent quarterly return
|DA|	=	Absolute value of discretionary accruals

The sample consists of 31,469 firm-year observations obtained with 5,678 unique firms for the period from 1996 to 2015.

Table-2. Estimation results of the no-switching model

$$RET_{i,t+1q} = \alpha + \beta \times |DA|_{i,t} + e_{i,t},\ e_{i,t} \sim N(0, \sigma)$$

	Estimate	S.D.	t-value	p-value
α	0.0028	0.0014	2.0368	0.0208
β	0.0143	0.0043	3.3072	0.0005
σ	0.2113	0.0008	251.5952	< 0.0001
Log-likelihood	4259.05			
AIC	4256.05			
Schwarz value	4243.51			

This table presents the estimation results of the no-switching model. See Table 1 for variable definitions and sample descriptions. σ is the standard deviation of the error term in the regression.

The statistics AIC＝ Log-likelihood function value – No. No. is the number of model parameters.

The statistics Schwarz value = Log-likelihood function value - (No./2) X ln(#). # is the number of sample.

Table-3. Estimation results of the switching regression model

$$RET_{i,t+1q} = \alpha_1 + \beta_1 \times |DA|_{i,t} + e_{1,it},\ e_{1,it} \sim N(0, \sigma_1),\ \text{if } s_{i,t} = 1$$
$$RET_{i,t+1q} = \alpha_2 + \beta_2 \times |DA|_{i,t} + e_{2,it},\ e_{2,it} \sim N(0, \sigma_2),\ \text{if } s_{i,t} = 2$$
$$prob\ (s_{i,t} = 1) = exp\ (\pi)/[1 + exp\ (\pi)]$$
$$prob\ (s_{i,t} = 2) = 1 - prob\ (s_{i,t} = 1)$$

	Estimate	**S.D.**	**t-value**	**p-value**
Regime I: $s_{i,t} = 1$				
α_1	0.0359	0.0017	21.7818	< 0.0001
β_1	0.0333	0.0049	6.8020	< 0.0001
σ_1	0.1332	0.0021	63.1185	< 0.0001
Regime II: $s_{i,t} = 2$				
α_2	-0.0519	0.0051	-10.2327	< 0.0001
β_2	-0.0087	0.0058	-1.4854	0.0687
σ_2	0.2874	0.0032	88.9907	< 0.0001
Probability parameter				
θ	0.4808	0.0628	7.6528	< 0.0001
Log-likelihood	5587.61			
AIC	5580.61			
Schwarz value	5551.36			
LR for $\beta_1 = \beta_2$	8.80*			
Probability of Regime I = 0.6179 (61.79%)				
Probability of Regime II = 0.3821 (38.21%)				

This table presents the estimation results of the switching regression model. See Table 1 for variable definitions and sample descriptions.

The statistics AIC＝ Log-likelihood function value – No. No. is the number of model parameters.

The statistics Schwarz value = Log-likelihood function value - (No./2) X ln(#). # is the number of sample.

To test the null hypothesis of $\beta_1 = \beta_2$, the switching regression model is first estimated on the basis of a two-state slope and $L(H_A)$, representing the log likelihood function. The model is then estimated assuming the existence of a single constant slope ($\beta_1 = \beta_2 = \beta$), which allows for the subsequent derivation of the log likelihood function of the restricted model, $L(H_0)$. Finally, this function is used to carry out a likelihood ratio test, $LR=-2[L(H_0)- L(H_A)]$. In terms of the null hypothesis, this test displays a χ^2 distribution with one degree of freedom. The * denotes the significance at the 1% level.