Distress Risk Anomaly and Misvaluation

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ABSTRACT

This paper examines the effects of misvaluation on the well-documented negative relation between distress risk and stock returns (distress risk anomaly). Findings indicate that distress risk is negatively related to stock returns only in the subset of the most overvalued stocks, which is consistent with mispricing explanations provided by prior studies. The distress anomaly disappears after controlling for mispricing effects. Further analysis reveals earnings management to be one possible cause for the overvaluation of highly distressed stocks. The results are robust to alternative specifications of distress risk and mispricing measures.

Keywords: Distress Risk, Mispricing, Earnings Management, Asset Pricing Anomalies

JEL Classification: G12; G14; G32; G33

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1. Introduction

The relationship between distress risk and stock returns has been the subject of increasing scholarly interest over the past two decades. Most studies reveal a negative impact of distress risk on stock returns (*e.g.*, Dichev, 1998; Campbell, Hilscher, and Szilagyi, 2008; Garlappi and Yan, 2011). This anomalous distress-return relation is in direct contradiction to the risk-reward trade-off in financial markets, which predicts that investors require a premium for bearing this type of risk, such as the holding of financially distressed firms in their portfolios (Fama and French, 1995; Chen and Zhang, 1998). A rational justification of the distress anomaly is that highly distressed firms earn lower returns due to the inability of investors to accurately price distressed stocks (Dichev, 1998; Griffin and Lemmon, 2002; Campbell *et al.*, 2008; Gao, Parsons, and Shen, 2018).

While studies concur that the distress anomaly is driven by mispricing, they do not investigate this argument in any particular depth. For example, in order to support the mispricing explanation, Griffin and Lemmon (2002) show that the anomaly is stronger during earnings announcements. In contrast, in documenting the distress anomaly, Campbell, *et al.* (2008) do not find supporting evidence consistent with the mispricing explanation. Specifically, they test the possibility that investors make valuation errors, overpricing these stocks because they fail to understand their poor prospects, but they do not find that valuation errors are corrected when distressed stocks make earnings announcements. Stambaugh *et al.* (2002) explore the role of investor sentiment in a broad set of anomalies in cross-sectional stock returns, including distress anomaly. They rely on a setting in which the presence of market-wide sentiment is combined with the argument that overpricing should be more prevalent than underpricing, due to short-sale impediments. They hypothesize that the anomalies, to the extent they reflect mispricing, should be stronger following high sentiment.

Therefore, although this study finds evidence consistent with the mispricing explanation of the distress anomaly, this is implied (indirectly) through this "sentiment-based" hypothesis. Elsewhere, Gao *et al.* (2018) examine and document the distress anomaly using a sample from 38 countries in order to test two competing explanations, one closely (but indirectly) linked to mispricing, and the second related to shareholder expropriation. Specifically, this study exploits the country-level variability with regards to overconfidence to show that the distress anomaly is explained by overconfident investors overpricing the stocks close to bankruptcy. It is therefore again an indirect test of mispricing under the assumption/hypothesis that overconfidence is closely linked to investors' overreaction (and consequently mispricing).

Furthermore, although Eisdorfer, Goyal, and Zhdanov (2019) provide theoretical and empirical evidence that equity misvaluation is driven by the mispricing of default options, they do not empirically associate these results with the distress risk anomaly. To the best of our knowledge, none of the prior studies directly investigate the mispricing explanation of the distress risk anomaly; instead they generally rely on indirect mispricing mechanisms and arguments to explain the distress anomaly. Our study aims to fill this gap using direct proxies of mispricing to examine whether the distress risk anomaly is driven by mispricing effects.

To provide supporting evidence in line with the mispricing explanation of the distress anomaly, we also examine whether the mispricing effect is more pronounced in firms with higher earnings management.[1] Motivated by studies that suggest financially distressed firms have more of an incentive to manipulate their financial performance in order to conceal (to some extent) their financial distress (DeAngelo, DeAngelo, and Skinner, 1994; Rosner, 2003; Lee and Yeh, 2004;

[1] This study, however, does not argue that earnings management is the unique source of mispricing. For example, Eisdorfer *et al.* (2019) conclude that default options are mispriced in equity values because investors do not fully recognize the option-like nature of equities and hence do not value them accordingly.

Charitou, Lambertides, and Trigeorgis, 2011), we test whether the mispricing explanation of the distress anomaly is stronger in firms with higher earnings treatments.[2] Highly distressed firms that engage in such practices shift their stock prices away from their fair (intrinsic) values. For instance, Jensen (2005) shows that the managers of overvalued stocks engage in earnings management practices to sustain overvaluation. Chi and Gupta (2009) and Badertscher (2011) concur with Jensen's (2005) findings. Further, Badertscher (2011) finds that, the longer a firm is overvalued, the more likely it is that the firm is engaged in earnings management practices.[3] Additionally, this analysis aims to provide one possible channel driving the mispricing explanation of the distress anomaly.

Our main mispricing proxy is based on the composite anomaly ranking measure by Stambaugh, Yu, and Yuan (2015), which is used widely by studies, especially in empirical asset pricing (*e.g.* Jacobs, 2016; Stambaugh and Yuan, 2017; Engelberg, Reed, and Ringgenberg, 2018).[4] The Stambaugh *et al.* (2015) mispricing measure is composited by 11 return anomaly factors, two of which are based on the financial distress measure of Campbell *et al.* (2008) and the bankruptcy probability O-Score of Ohlson (1980).[5] Consequently, these two distress factors are excluded from our calculation of the mispricing measure, in order to control for any mechanical bias in the investigation of the distress risk anomaly. This mispricing measure is directional, meaning that it

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[2] Other studies show that earnings shenanigans are used by firms to keep financial constraints and external financing cost at low levels (Lamont, Polk, and Saá-Requejo, 2001; Livdan, Sapriza, and Zhang, 2009).
[3] Earnings management is unsustainable, as the negative financial information can only be withheld until it reaches some arbitrary level. Once reached, firms experience a stock price reduction, or even a crash (Kothari, Shu, and Wysocki, 2009). For example, Hutton, Marcus, and Tehranian (2009) show that firms with high accounting opacity (proxied for earnings management) have a higher probability of stock price crash, which is another form of risk.
[4] We would like to thank the anonymous referee for suggesting this mispricing measure.
[5] Stambaugh *et al.* (2015) use the proposed misipricing measure as a potential explanatory variable of idiosycratic volatility and show that idiosycratic volatility is negatively related to stock returns among overpriced stocks and positive among underpriced stocks. In an earlier study, Stambaugh *et al.* (2012) show that the distress anomaly (long-short strategy) is more pronounced during high investor sentiment periods, suggesting that, during high investor sentiment periods, stocks tend to be overvalued (Baker and Wurgler, 2006).

is able to capture the sign of the misvaluation (*i.e.* undervalue vs. overvalue). This feature is essential in our study as it allows us to identify whether the distress anomaly is driven by undervalued or overvalued stocks.

We also utilize two alternative measures of mispricing. The first is the mispricing proxy derived from the residual income model of Rhodes-Kropf, Robinson, and Viswanathan (2005) that is widely used (Bonaimé, Öztekin, and Warr, 2014; Doukas, Kim, and Pantzalis, 2010a; Warr, Elliott, Koëter-Kant, and Öztekin, 2012).[6] Our second alternative mispricing measure is the dispersion in analysts' earnings forecasts (*e.g.*, Diether, Malloy, and Scherbina, 2002; Johnson, 2004; Sadka and Scherbina, 2007). Johnson (2004) shows that a negative relationship between dispersion of earnings expectations and stock returns is more pronounced for more financially-levered firms, which is an important determinant of firms' distress risk (Ohlson, 1980; Campbell *et al.*, 2008). This result is consistent with our hypothesis that the negative distress-return relation is driven primarily by misvalued stocks.

A basic way to proxy for distress risk is to use the option pricing model outlined by Black and Scholes (1973) and Merton (1974). The model views equity as an option on the firm's assets with exercise price the face value of debt. This measure, in contrast to the alternative reduced-form models of Altman (1968) and Ohlson (1980), is a forward-looking measure of a firm's likelihood to default (Vassalou and Xing, 2004). Our primary distress risk measure is based on the naïve approach by Bharath and Shumway (2008). For robustness, we also utilize two alternative distress risk measures, a) the modified option-based distress risk measure following Charitou, Dionysiou, Lambertides and Trigeorgis (2013), and b) the failure score by Campbell *et al.* (2008) estimated by a dynamic logit model.

[6] Rhodes-Kropf *et al.* (2005) show that misvaluation is a key driver of merger activity, which is still robust after they control for neoclassical explanations of takeover.

Our findings show that the distress risk anomaly is driven primarily by mispriced stocks, which supports arguments made by prior studies (Dichev, 1998; Griffin and Lemmon, 2002; Gao *et al.* 2018). We additionally show that the negative distress–return relationship is primarily caused by the overvaluation of highly distressed stocks. That is, overvalued stocks are more likely to have lower or even negative returns in subsequent month(s). Our findings also suggest that the upwards earnings management of distressed firms is one possible channel of the distress risk anomaly. Our findings are robust to alternative distress and mispricing measures.

The main contribution of this study is threefold: first, we provide direct evidence of the mispricing explanation to the 'distress risk puzzle', indicating that the distress risk anomaly is driven by overvalued stocks (a systematic feature of highly distressed stocks); second, by properly controlling for mispricing effects, we show that the distress risk–return anomaly can be resolved; last, we show that the interconnection between distress risk and mispricing can be explained by firms' earnings management.

The remainder of the paper is organized as follows: section 2 reviews the extant literature, section 3 describes the data, the measurements of the variables and the adopted methodology, section 4 discusses the empirical results and presents a robustness analysis, and section 5 provides a conclusion.

2. Literature Review

The distress risk anomaly has been at the center of a number of asset pricing studies over the last three decades (Chan and Chen, 1991; Fama and French, 1996; Dichev, 1998; Campbell, *et al.* 2008; Garlappi and Yan, 2011). For instance, Fama and French (1992; 1993) argue that value premium can be explained by financial distress, however, this argument goes against the majority of studies on the reported impact of distress risk on stock returns. Dichev (1998) shows a negative relationship between default risk and stock returns using the Altman (1968) and Ohlson (1980) scores of probability of default. He attributes the anomaly to the inability of investors to accurately price distress risk, however, he does not provide a direct test on the mispricing explanation. Griffin and Lemmon (2002) show that firms with high distress risk tend to have the largest return reversals around earnings announcements, which is an implicit justification of the mispricing hypothesis. On the contrary, Campbell *et al.* (2008) show that the negative distress risk–return relationship is not concentrated around earnings announcements, but still attribute the distress anomaly to investors' overvaluation errors. A recent study by Gao *et al.* (2018) attributes the distress risk anomaly to the (temporary) overpricing of distressed stocks driven by investors' overconfidence and underreaction behavior. Garlappi, Shu, and Yan (2008) and Garlappi and Yan (2011) explain the distress risk anomaly through the renegotiation options available to shareholders close to the bankruptcy event. Likewise, Bali, Del Viva, Lambertides, and Trigeorgis (2019) argue that the reorganization (put) options lead firms to higher (returns) skewness, which result in lower stock returns. Conrad, Kapadia, and Xing (2014) argue that the negative distress–return relationship arises due to the high probability of distressed firms' jackpot payoffs.

On the other hand, some studies (Vassalou and Xing, 2004; Chava and Purnanandam, 2010; Aretz, Florackis, and Kostakis, 2018) find a positive relationship between distress risk and stock returns. For instance, Vassalou and Xing (2004) show that the relationship between default risk and stock returns turns positive for small (capitalization) and high book-to-market firms. Also, Da and Gao (2010) demonstrate that the positive relationship between stock returns and default risk occurs only in the first month following portfolio formation, but two months later, the default risk premium disappears. They argue that this positive relationship is driven by short-term reversals instead of systematic default risk. Overall, the negative distress–return relation is more prevalent.

Aretz *et al.* (2018), using a novel bankruptcy sample for non-U.S. firms in 14 developed markets find a positive distress–return relationship. Further, they show that this positive relationship is driven by the idiosyncratic component of distress risk and it is more pronounced in countries with a stronger creditor protection framework and lower bargaining power of shareholders.

Eisdorfer *et al.* (2019) provide evidence of a relation between default risk and misvaluation. Their study shows that equity misvaluation is associated with the inability of investors to properly incorporate the value of the option to default in equity prices. This finding provides further support on the real options-based explanations related to the distress risk anomaly suggested by prior studies (Garlappi, *et al.* , 2008; Garlappi and Yan 2011; Bali *et al.*, 2019). Eisdorfer *et al.* (2019), however, do not investigate the role of misvaluation on the distress risk–return puzzle. Some other studies implicitly link mispricing with distress. For example, Gao *et al.* (2018) connect mispricing with distress risk through investors' underreaction to recent bad news of highly distressed stocks. By developing two proxies of bad news to capture the stocks' (relative) mispricing due to investors' reaction on new information, they show that investors' underreaction to recent bad news lead distressed firms to temporarily mispricing (overvalued) levels.

From another perspective, Johnson (2004) uses analysts' dispersion to proxy for mispricing and argue that the negative relation between analysts' dispersion and returns is more pronounced when firms have high levels of debt, while Altman (1968), Ohlson (1980) and Campbell *et al.*, (2008), among others, show that firms' leverage is a significant determinant of financial distress.[7] These findings indirectly concur with a correlation between distress risk and mispricing. Along

[7] Several studies use analysts' dispersion/disagreement as a proxy for mispricing. For instance, Sadka and Scherbina (2007) use analysts' disagreement as a proxy for mispricing and show that stocks diverge from their intrinsic values when the trading costs are high, which is consistent with prior studies (*e.g.*, De Long, Shleifer, Summers, and Waldmann, 1990; Pontiff, 1996; Shleifer, 2000). Diether *et al.* (2002), using the same mispricing measure, show a negative relation between mispricing and subsequent stock returns.

the same lines, Avramov, Chordia, Jostova, and Philipov (2009) show that the profitability of dispersion-based (mispricing) trading strategies is driven by the worst-rated firms directly associated with financial distress. Overall, evidence shows that stock mispricing and financial distress are interconnected, something that needs further investigation in the context of the distress anomaly.

3. Data, Measurements and Methodology

3.1. Sample Data

Our initial sample includes 8,852 U.S. firms from the period of January 1976 to December 2015, utilizing the data available from the Compustat (Quarterly) and CRSP databases (excluding financial firms with 4-digit SIC codes between 6000 and 6999).[8] To ensure that accounting variables are known before the monthly market data (*e.g.* returns), we match quarterly accounting data with stock returns three months after the fiscal quarter-end. Our analysis is based on monthly observations, which provides us the opportunity to capture the dynamic effects of distress risk (Chava and Jarrow, 2004).

3.2. Distress Risk

The most appropriate proxy of distress risk for this research question is the Black and Scholes (1973) and Merton (1974) (hereafter BSM) option-based probability to default. An advantage of using option models in calculating the distress risk is that they provide the necessary structure to infer default-related information from market prices. Option pricing models enable the construction of a measure of distress risk that contains forward-looking information (since market

[8] All the quarterly variables derived from Income statements and Cash Flows are calculated based on Trailing Twelve Months (TTM), thus the variables are all seasonally adjusted.

prices reflect investors' expectations about a firm's future performance). This is more appropriate for estimating the market´s assessment of the likelihood of a firm exercising its default option in the future than historical estimates. Unlike accounting-based (reduced form) models, firm asset volatility is a key input in such option pricing models.[9]

In this paper, distress risk is measured using the Bharath and Shumway (2008) approach. Specifically, we use the distance to default (hereafter *DD*) that is derived from Merton *DD* equations.

$$DD_{BhSh}=\frac{ln\left(\frac{V}{B}\right)+\left(R_{t-1}-0.5\sigma^2_{v(BhSh)}\right)T}{\sigma_{v(BhSh)}\sqrt{T}} \tag{1}$$

where V is the firm assets' value that equals to the firm's market value of equity (ME), plus the face value of its debt (B). The market value of equity (ME) is the number of shares outstanding (CRSP item "shout") multiplied by the market price of shares (CRSP item "prc"), while the face value of debt is estimated using the debt in one year (Compustat item "dd1"), plus half long-term debt (Compustat item "dltt") which is the same debt variable that is used by Crosbie and Bohn (2003) in their *KMV* model. R_{t-1} is the annual stock returns (CRSP item "ret") at month t-1. The firm volatility ($\sigma_{v(BhSh)}$) is estimated as a weighted average of the volatilities of a firm's equity and debt: $\sigma_{v(BhSh)}=\left(\frac{ME}{(ME+B)}\right)\sigma_E+\left(\frac{B}{(ME+B)}\right)\sigma_B$.

Equity volatility (σ_E) is derived from monthly equity returns, adjusted for cash dividends[10] over a 36-month window: $R_E=ln\left(\frac{E_t+CD_t}{E_{t-1}}\right)$, while debt volatility is estimated using an approximation

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[9] For the past half century, scholars, recognizing the importance of bankruptcy probability in the investment world, have often attempted to find the most efficient way to measure it. These measures are separated into two main categories: reduced-form models and structural models (Charitou, Lambertides, and Trigeorgis, 2008). The most widely used reduced-form models are those using Altman's (1968) and Ohlson's (1980) scores. The seminal study by Black and Scholes (1973) and Merton (1974) was the trigger for many scholars to investigate the default probabilities and their consequences using option pricing-based models. The BSM model is considered to be the first structural model.

[10] CD_t is cash dividends (Compustat item "dvpsx").

formula $\sigma_B=0.05+0.25\sigma_E$. T is the maturity time of a firm's equity option, which is set to one for consistency.

For robustness, we use two alternative distress risk measures: a) the default risk by Charitou *et al.* (2013) (DD_{CDLT}), and b) the failure probability by Campbell *et al.* (2008), DR_{CHS}. DD_{CDLT} is estimated similarly to Bharath and Shumway (2008), save for the calculation of firm's volatility ($\sigma_{v(CDLT)}$). In particular, $\sigma_{v(CDLT)}$ is estimated from the firm value return, which is obtained as $R_V=ln\left(\frac{V_t+D_t}{V_{t-1}}\right)$, where D_t is the total firm payout at time t that equals to cash dividends plus interest expenses (Compustat item "xint"). Finally, the volatility ($\sigma_{v(CDLT)}$) of R_V is estimated by using a 36-month window. The second alternative distress risk measure DR_{CHS} is estimated by a dynamic logit model similar to that by Campbell *et al.* (2008) using both accounting and market explanatory variables to forcecast the 12-month-ahead probability to default. All distress risk measures are estimated at a monthly frequency.

3.3. Mispricing Measures

Our primary mispricing measure is the composite mispricing measure suggested by Stambaugh *et al.* (2015). This mispricing proxy is based on 11 return anomalies reported in the literature. In this study we use nine of them, as the remaining two are related to firms' financial distress, namely the financial distress risk by Campbell *et al.* (2008) and Ohlson (1980). More specifically, our mispricing measure is based on the following 9 return anomalies:

1) Net stock issues (Fama and French, 2008)
2) Composite equity issues (Daniel and Titman, 2006)
3) Total accruals (Sloan, 1996)
4) Net operating assets (Hirshleifer, Hou, Teoh, and Zhang, 2004)
5) Gross profitability (Novy-Marx, 2013)
6) Asset growth (Cooper, Gulen, and Schill, 2008)

7) Momentum (Jegadeesh and Titman, 1993)
8) Return on assets (Fama and French, 2006)
9) Investment-to-assets (Lyandres, Sun, and Zhang, 2008; Xing, 2008)

Similarly to Stambaugh *et al.* (2015), using the key variables derived from the above anomalies (lagged by one-month) we first rank stocks on a monthly basis.[11] Next, we estimate the average rank for each firm-month observation. This process gives the univariate composite anomaly ranking, *SYY*.

For robustness, we use two alternative proxies to reduce bias inferences that may occur due to a potential measurement error. The first alternative mispricing measure is based on the decomposition method of a firm's market-to-book ratio developed by Rhodes-Kropf *et al.* (2005). Specifically, we decompose the firm's natural logarithm of market-to-book equity ratio, *ln(M/B)*, into two components: the misvaluation (market value to intrinsic value of equity) and the growth option (intrinsic value to book value of equity) components (Hertzel and Li, 2010). The decomposition formula is as follows:

$$ln\left(\frac{M}{B}\right) = ln\left(\frac{M}{V}\right) + ln\left(\frac{V}{B}\right) \tag{2}$$

where M is the stock market capitalization, B stands for the book value of common equity, and V represents the intrinsic value of equity which needs to be estimated. In contrast to prior studies (Lee, Myers, and Swaminathan, 1999; Dong, Hirshleifer, and Richardson, 2006), Rhodes-Kropf *et al.* (2005) relax the residual income model to estimate V (by excluding analysts' forecasts), thus greatly reducing the bias level of the estimations. The residual income specification is as follows:

$$ln(M_{i,t}) = a_{0jt} + a_{1jt} \times ln(B_{it}) + a_{2jt} \times ln(|NI_{it}|) + a_{3jt} \Gamma\, ln(|NI_{it}|) + a_{3jt} \left(\frac{TL}{MV}\right)_{it} + \varepsilon_{it} \tag{3}$$

[11] A brief description of these variables is given in Appendix A1.

where $|NI_{it}|$ is the absolute value of net income (Compustat item "ni") of firm i at time t. I^{-} is a binary variable that equals to one for firms with negative net income and zero otherwise. *D/MV* is the market leverage ratio that equals to the firm's total liabilities over the market value, *MV*. *MV* is equal to the firm's market capitalization—deferred taxes (Compustat item "txdb")—book value of common equity (Compustat item "ceq"). Subscript j refers to the industry. ε_{it} captures the difference between the observed market value of equity and intrinsic value. The estimated residual term of Eq. (3), $\hat{\varepsilon}_{it}$, is the proxy for misvaluation and is abbreviated as *RRV* in the empirical analysis. Eq. (3) is estimated cross-sectionally for each industry and month. We use the 12-industry classification scheme by Fama and French (1997). This model specification (Eq. 3) can explain the within-industry cross-sectional variations of market capitalization (*M*) by an average of over 89% for all industries. This misvaluation measure has also been employed by other studies (Hertzel and Li, 2010; Fu, Lin, and Officer, 2013).

Our second alternative mispricing proxy is the analysts' disagreement (or forecast dispersion), *DIS*, that has been widely used (*e.g.*, Johnson, 2004; Sadka and Scherbina, 2007). Following previous studies (Diether *et al.*, 2002; Johnson, 2004; Sadka and Scherbina, 2007), we define analysts' disagreement as the standard deviation of all outstanding earnings-per-share forecasts for the current fiscal year over the absolute value of the mean outstanding earnings forecasts (zero values of the average forecasts are excluded).[12] This measure is calculated solely for firms covered by at least two analysts.

3.4. Methodology

Our methodology is divided into a portfolio and a Fama-MacBeth regression analysis. The preliminary, univariate portfolio analysis aims to show the existence of the distress anomaly. In

[12] Analysts' earnings forecasts are collected from the U.S. Institutional Brokers Estimate System, known as I/B/E/S.

the double-sorted portfolio analysis, we identify potential interconnections between stock mispricing and distress risk. In the single-sort portfolio analysis, stocks are sorted into ten portfolios based on distress risk measures. In the double-sort portfolio analysis, stocks are first sorted into five portfolios based on mispricing measures and then, within each mispricing portfolio, stocks are sorted into five portfolios based on distress risk.

In the second part, we run Fama and MacBeth (1973) regressions by augmenting the standard Fama and French model with distress risk, mispricing and some interaction terms. Our basic regression specification is as follows:

$$EXRET = f\,(BETA, SIZE, BM, ROE, MOM, DR, SYY, Interactions) \quad (4)$$

where *EXRET* is the monthly stock excess (over risk-free rate) return in percentage. *BETA* represents the firm's systematic risk estimated over the previous 36 months, using the traditional capital asset pricing model (CAPM). *SIZE* is the firm's monthly market capitalization estimated as the natural logarithm of *ME* (which is equal to a stock's price multiplied by the number of shares). *BM* is book-to-market ratio estimated as the book value of common equity divided by *ME*. *ROE* is the ratio of return-on-equity estimated as a firm's net income to book value of common equity. *MOM* stands for momentum calculated as the cumulative monthly return of the previous 6 months leaving one month as a gap. *DR* is distress risk, the negative distance-to-default (DR_{BhSh}), as derived from Eq. (1).[13] *SYY* is the 'composite anomaly ranking' mispricing measure by Stambaugh *et al.* (2015). All explanatory variables are lagged by one month (*t-1*). To avoid sensitivity of our results to extreme observations, we perform the analysis winsorizing the top and bottom 1% (1st and the 99th percentiles, respectively) of observations for each independent variable.

[13] Similarly, the negative DD_{CDLT} is abbreviated as DR_{CDLT}.

4. Empirical Analysis

Subsection 4.1 presents the summary statistics of our key variables, along with portfolio analysis to investigate distress anomaly. Subsection 4.2 presents the Fama-MacBeth analysis, whereas subsection 4.3 provides a possible explanation of the mispricing effect in distress risk anomaly through earnings management. Finally, subsection 4.4 presents the robustness analysis of this study. If our hypothesis that distress risk anomaly is driven by overvalued stocks is valid, then after controlling for mispricing effects, the distress anomaly should be eliminated.

4.1 Summary Statistics and Portfolio Analysis

Table 1 reports descriptive statistics (Panel A) and correlation coefficients (Panel B) for our key variables. *BETA* is the systematic risk and is close to one (mean=1.12 and median=1.06). The average *SIZE* (ln(*ME*)) is 5.25, ranging from 0.28 to 10.19. *BM* has an average value equal to 0.74 which is close to other studies (*e.g.*, Kothari and Shanken, 1997; Trigeorgis and Lambertides, 2014). The mean values of *ROE* and *MOM* are equal to 1.6% and 12.8%, respectively. Mean *DR* is -6.01, which is quantitatively similar to other studies that use a similar *DR* measure (*e.g.* Bali *et al.*, 2019). *SYY* has a mean of 0.48, while its median is very close to its mean value. Panel B shows that *SIZE* is negatively correlated with *BM* (-0.413) and *DR* (-0.356). In general, all bivariate correlation coefficients are relatively small (|corr. coef. |≤ 35.6%).

[Insert Here Table 1]

Table 2 presents a portfolio analysis that is divided into single and double-sorted. Panel A shows raw and risk-adjusted (value-weighted) returns based on our main distress and mispricing measures, DR_{BhSh} and *SYY*.[14] Stocks are sorted into ten portfolios based on DR_{BhSh} and *SYY* of the previous month and the value-weighted return of each portfolio is reported (with monthly rebalancing). Consistent with prior studies, we find a negative relationship between distress risk and stock returns (*e.g.*, Campbell *et al.*, 2008; Garlappi and Yan, 2011). The raw and risk-adjusted return difference between the highest and lowest *DR* portfolios are -0.82 (*t*-stat = -2.70) and -1.45% (*t*-stat = -5.46), respectively.[15,16] The results for our main mispricing measure, *SYY*, show that both raw and risk-adjusted returns difference between the highest and lowest mispricing portfolios is negative and highly significant. This indicates that stocks in the most overvalued portfolios (10th) tend to underperform, compared to those in the most undervalued portfolios (1st) based on *SYY*.

To examine the role of mispricing in the distress risk anomaly, we perform double-sort portfolio analysis, as presented in Panels B1 and B2 of Table 2. Stocks are first sorted into five portfolios based on the mispricing measure (*SYY*) of the previous month and subsequently into five distress risk portfolios.[17] Panel B1 illustrates the results based on raw returns, while Panel B2 shows the corresponding risk-adjusted returns based on the Fama and French five-factor model. Panels B1 and B2 of Table 2 show that the negative distress risk–return anomaly exists in the most overvalued

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[14] Risk-adjusted returns are estimated by the five-factor model of Fama and French (2015). Untabulated results derived from alternative asset pricing models such as CAPM and the Fama and French (1993) three-factor model are qualitatively similar.

[15] The risk-adjusted return is derived from the Fama and French five-factor model as follows:

$$EXRET_{j,t}=RA\_RET_{jt}+\beta_{j,MRP}\times MRP_t+s_{j,SMB}\times SMB_t+s_{j,GHML}\times HML_t+r_{j,RMW}\times RMW_t+c_{j,CMA}\times CMA_t+\varepsilon_{j,t}$$

where $EXRET_{j,t}$ is the portfolios' *j* excess return (over one-month risk-free rate) in month *t*. *MRP* is market risk premium in the U.S. *SMB* is the small-minus-big and *HML*, the high-minus-low factors that account for the return difference between small- and big-sized firms, and value and growth stocks, respectively. *RMW* (robust minus weak) stands for the profitability factor and *CMA* (conservative minus aggressive) represents the investment factor. The Fama-French risk factors, along with the risk-free interest rate are obtained from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. RA_RET_j captures the abnormal or risk-adjusted returns of the portfolio *j* that are not explained by the risk factors.

[16] The *t*-statistics are based on Newey and West (1987) standard errors with six lags. The *t*-statistics are qualitatively similar based on White's (1980) standard errors.

[17] The untabulated results based on independent double-sorting portfolios are qualitatively similar.

(5-highest) mispricing *SYY* portfolio. The risk-adjusted return difference between the lowest and highest distressed portfolios in the most overvalued portfolio is -1.01% (or -11.47% per annum), which is highly statistically significant. On the other side of most undervalued stocks, the high distressed stocks seem to perform better than the low distressed stocks (however insignificant for risk-adjusted returns). These findings explicitly set out the mispricing hypothesis of distress risk anomaly in that the latter seems to be forced/driven by the inevitable market correction of highly distressed (overvalued) stocks.

[Insert Here Table 2]

These preliminary findings suggest that mispriced stocks affect the distress anomaly, which is consistent with our initial hypothesis. Taking into account the explanation of prior studies (Gao *et al.*, 2018; Stambaugh *et al.*, 2012 and 2015) on the mispricing hypothesis, we can assume that the negative distress anomaly is driven by the price correction of extremely overvalued distressed stocks. Overall, these results encourage further investigation of the distress risk and mispricing explanation.

4.2 Fama-MacBeth Regression Analysis

In this section, we examine whether distress risk explains subsequent stock returns beyond several known control variables using Fama-MacBeth regression analysis. These results are presented in Table 3.[18] First, in Models (1) and (2) we confirm the role of standard variables (*e.g.*, *BETA*, *SIZE*, B/M) in a basic Fama and French (1992) type analysis (including *ROE* and *MOM*). Then, we proceed with our extended analysis of the incremental role of distress risk in explaining subsequent equity returns. Consistent with prior studies, both *SIZE* and *BM* are significant (with

[18] The reported *t*-statistics in our Fama-MacBeth regressions are based on Newey and West's (1987) estimated standard errors.

the correct sign) in explaining subsequent returns. *ROE* and *MOM* are also positive and highly significant. Model (3) confirms that distress risk (DR_{BhSh}) exhibits a significant *negative* relation with subsequent equity returns: a unit increase in DR_{BhSh} implies a lower average return by 2.2%. Models (4) and (5) examine the impact of distress risk on subsequent returns after controlling for mispricing. Consistent with prior studies, *SYY* is negative and highly significant (*e.g.* Doukas *et al.*, 2010*;* Stambaugh *et al.*, 2015), that is, overvalued stocks tend to have a lower subsequent return. The distress risk impact on stock returns becomes insignificant when it is added with mispricing in Model (4). In order to examine the interconnection between distress risk and mispricing, their interaction term is added in Model (5). Consistent with our expectations, the negative sign of the interaction term (coef. = -0.12, *t*-stat = -8.34) in Model (5) shows that overvalued distressed firms tend to have lower average returns. The sign of DR_{BhSh} turns to be positive and significant, implying a positive distress impact on returns for most undervalued stocks; however, the impact of most overvalued stocks (*i.e.*, the sum 0.053-0.122 = -0.069) is more negative and statistically significant. This result is consistent with the overall negative distress risk–return relation (documented in Model (3) and prior studies); moreover, it confirms that this is mainly driven by overvalued stocks.

In Panel B of Table 3, we further investigate the relation between DR_{BhSh} and stock returns by running Fama-MacBeth regressions within five mispricing portfolios sorted by *SYY*.[19] This panel shows that the impact of the distress risk of the most undervalued portfolio (P_1) is positive (coef. = 0.017) and marginally significant (at 10% level), consistent with the positive distress-return relation based on raw returns shown in Panel B1 of Table 2. The three middle mispricing portfolios (P_2-P_4) show that DR_{BhSh} is not significant in explaining subsequent stock returns. On the other

[19] The results are qualitatively similar regardless of the mispricing measure.

hand, the impact of the distress risk on returns of the most overvalued portfolio (P_5) is negative (coef. = -0.06) and highly significant (t-stat = -3.61). These results corroborate our previous findings that the distress risk anomaly is mostly driven by overvalued stocks.

[Insert Here Table 3]

4.3 Distress Risk Anomaly, Mispricing and Earnings Management

Consistent with prior studies, we argue that a possible cause of mispricing, that seems responsible for the distress risk anomaly, is unusual (upwards) earnings management (EM) in highly distressed firms.[20] Prior studies (*e.g.*, Charitou *et al.*, 2007, 2011; Lee and Yeh, 2004;) show that distress risk is positively related to earnings management. Other studies (Xie 2001; Jensen, 2005; Chi and Gupta, 2009; Badertscher, 2011) show that EM is positively related to mispricing (overvaluation). Based on this literature, it is natural to examine whether upwards earnings management is a possible channel for the documented negative relation between distress risk and stock returns driven by overvalued stocks. To investigate this channel, we re-estimate our base Model (5) of Table 3 using three different proxies of earnings management. Our three EM measures are based on a) the total accruals by Sloan (1996), b) the modified Jones discretionary accruals of Dechow *et al.* (1995), and c) the performance-matched discretionary accruals of Kothari, *et al.* (2005). Similar to Hutton *et al.* (2009), our EM measures are defined as the three years moving sum of the corresponding accruals measure: a) *ACCR3YR*, b) *DACCR3YR*, and c) *PM_DACCR3YR*.[21,22] We

[20] The earnings management channel is by no means exclusive. For example, untabulated additional analysis corroborates the argument that arbitrage risk may be one dimension of mispricing that, at low levels, caused the distress anomaly to disappear. This suggests that another possible force or mechanism of the mispricing of distressed firms, and consequently of the distress anomaly, is limits-to-arbitrage (proxied by idiosyncratic volatility). These findings are consistent with those of Stambaugh *et al.* (2015), who show that the negative idiosyncratic volatility–return relationship in stocks is driven by overvalued stocks. We thank an anonymous referee for pointing out this dimension of our findings.
[21] The definition of EM measures is described in detail in Appendix A2.
[22] Hutton *et al.* (2009) defines financial opacity as the three-year moving sum of the absolute discretionary accruals estimated from the modified Jones (1991) model.

avoid to use the absolute values as in Hutton *et al.* (2009), because the direction (*i.e.* upwards or downwards) of earnings management is highly important in our setting. To examine whether the level of earnings management of overvalued stocks is one possible channel of the distress risk anomaly, we re-estimate our base Model (5) within high and low EM portfolios. The High EM portfolio consists of firms in the fifth EM quintile, and the Low EM portfolio consists of firms in the first EM quintile. All EM portfolios are constructed using 12-month lags.

Table 4 presents the results for each EM portfolio. The results show that the interaction term $DR \times SYY$ is negative and significant only for high EM firms. For low EM firms, the interaction term is insignificant. The results are consistent based on all three earnings management proxies. These results show that the distress risk anomaly, found to be driven by overvalued stocks in Table 3, exists only in firms with consistently upwards earnings management. This confirms our argumentation that one possible source of the overvaluation of distressed firms (that causes the distress risk anomaly) is the unusual upwards earnings management of these firms, which is also consistent with the related literature (*e.g.*, Rosner, 2003; Charitou *et al.*, 2007, 2011; Chi and Gupta, 2009; Badertscher, 2011).

[Insert Here Table 4]

4.4 Robustness Analysis

First, we provide robustness tests by re-running the double-sorted portfolio using alternative proxies for distress risk and mispricing.[23] Table 5 presents the double-sorted portfolio analysis using the alternative distress and mispricing measures.[24] This analysis provides additional evidence on the interconnection between *DR* and stock mispricing based on the alternative distress

[23] Appendix A2 also shows the (single-sort) univariate analysis using alternative distress and mispricing measures. The results are qualitatively similar with those in the main analysis (Panel A, Table 2).

[24] For convenience, Table 5 presents only the risk-adjusted returns. The corresponding results using raw returns are qualitatively similar (untabulated).

risk measures DR_{CDLT} and DR_{CHS} (in Panel A) and alternative mispricing proxies *RRV* and *DIS* (in Panel B), calculated as described in sections 3.2 and 3.3, respectively. All findings in Table 5 are consistent with our main results in Table 2 based on any alternative measure, confirming that the negative distress risk anomaly is more prevalent within the most overvalued portfolio.

[Insert Here Table 5]

Table 6 illustrates the Fama-MacBeth regression results using the alternative distress and mispricing measures.[25] Consistent with Table 3, the interaction term of the distress and mispricing measures is negative and statistically significant in all model specifications based on any alternative distress and mispricing measure.[26]

[Insert Here Table 6]

To examine further the robustness of our findings, we next isolate the "pure" component of distress risk from potential (undesired) mispricing effects. If our inference is true, we expect the new "*pure*" distress risk to be insignificant in explaining subsequent stock returns. To do this decomposition, we run DR_{BhSh} on SYY using the following OLS:[27]

$$DR_{BhSh,i,t}=a_{j,t}+\delta_{j,t}SYY_{i,t}+\varepsilon_{i,t} \tag{5}$$

The "*pure*" *DR* (DR^{SYY}_{BhSh}) is the estimated residuals ($\hat{\varepsilon}_{i,t}$) of Eq. (5). This captures the information of distress risk that is not explained by the mispricing variable, *SYY*. Similarly, we calculate the "*pure*" *DR* based on the alternative measures of distress risk (DR_{CDLT} and DR_{CHS}) and mispricing (RRV and *DIS*).

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[25] Table 6 also presents the base Model (5) from Table 3 for comparison.

[26] Further, we re-estimate Models (3) to (5) of Table 3 using the default probability measure of Vassalou and Xing (2004), where the untabulated results are qualitatively similar.

[27] We run each regression for each month (*t*) and industry (*j*) (using the 48-industry classification of Fama and French (1997)) in order to capture the industry-specific distress characteristics that play a key role in distress risk determination (Chava and Jarrow, 2004). The same exists for mispricing measures within each industry (Alford, 1992; Liu, Nissim, and Thomas, 2002).

These results are presented in Table 7.[28] The first three models include the original ("contaminated") distress risk measures, DR_{BhSh}, DR_{CDLT}, and DR_{CHS} which are replaced by DR_{BhSh}^{SYY} DR_{CDLT}^{SYY} and DR_{CHS}^{SYY} in Models (4) to (6), respectively. The "*pure*" distress risk measures in Models (4) to (6) are derived from the Eq. (5) using our primary mispricing measure. These models indicate that the "*pure*" distress risk measures are insignificant, confirming our expectations that by removing the mispricing effect from *DR* the negative distress–return relation disappears. The results remain robust using the alternative measures of mispricing in Models (7) and (8).

Overall, the results provide evidence that distress risk anomaly is likely due to overvalued distressed stocks that tend to decline in the following month(s). Our findings are consistent with Gao *et al.* (2018), who argue that distress risk anomaly is driven by temporarily overpriced distressed stocks. In this line of thought, our study shows that the distress risk anomaly disappears if the mispricing effect is properly treated, supporting the mispricing hypothesis of prior studies in explaining the distress risk anomaly (Dichev, 1998; Griffin and Lemmon, 2002; Campbell *et al.*, 2008).

[Insert Here Table 7]

5. Conclusion

Several studies suggest that distress risk is negatively related to stock returns (*e.g.*, Campbell, 2008; Garlappi and Yan, 2011). Our study investigates this anomalous relation and contributes to the existing literature by directly examining whether distress risk is affected by mispricing effects.

[28] In this analysis, we maintain a common sample across all models to allow for consistent comparisons.

Our argument is also motivated by the fact that prior studies relied upon indirect mispricing justifications to explain distress anomaly (Dichev, 1998; Griffin and Lemmon, 2002).

Our findings suggest that distress anomaly is driven by mispriced (overvalued) stocks, which is consistent with prior studies (Dichev, 1998; Griffin and Lemmon, 2002) that attribute the distress anomaly to the inability of investors to accurately price distress risk. Our results provide evidence that the negative distress–return relation exists only within the portfolio of the most overvalued stocks. By decomposing the mispricing effects from distress risk through an OLS regression, we find that the "*pure*" (net of mispricing effects) distress risk does not have any significant effect on stock return, confirming our hypothesis that distress risk anomaly is driven by mispricing effects. Furthermore, we provide evidence that the overpricing phenomenon of highly distressed stocks is associated with upwards earnings management of financially troubled firms, as shown using three different earnings management measures. The results are robust to alternative specifications of distress risk and mispricing proxies.

In terms of contributions, our study is the first to provide direct evidence of the mispricing explanation to the distress risk anomaly, showing that the negative distress risk–return relationship is driven by overvalued stocks. The mispricing effect is probably the main cause of other asset pricing anomalies as well, which can be investigated by following a methodology similar to the one in this study. Moreover, the findings of this study are highly important for institutional investors who use distress risk as a key driver in formulating their investment strategies; they are facilitated in better screening distress stocks and thus avoiding investment in overvalued distressed stocks that may lead to poor performance.

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Table 1
Summary Statistics of Key Variables

This table presents summary statistics (Panel A) and correlation coefficients (Panel B) for the key variables that are included in the asset pricing model specified by Eq. (4). *RET* is monthly stock returns derived from CRSP Database. *BETA* is estimated using the CAPM over a 36-month period. *SIZE* is the natural logarithm of market capitalization (number of shares outstanding × price per share). Book-to-Market (*BM*) ratio is the book value of common equity divided by market capitalization. *ROE* (Return-on-Equity) is equal to net income over book value of common equity. *MOM* (Momentum) is estimated as the cumulative monthly return of the previous 6 months leaving a one-month gap. DR_{BhSh} is the negative distance to default which is estimated by Eq. (1). *SYY* is the mispricing measure calculated as the composite ranking measure based on 9 return anomalies similar to Stambaugh *et al.* (2015). All the variables apart from the return are lagged by one month. Panel B presents the Pearson correlation coefficients. ** and * represent statistical significance at 1% and 5% respectively.

Panel A. Summary Statistics

	RET	***BETA***	***SIZE***	***BM***	***ROE***	***MOM***	DR_{BhSh}	***SYY***
Mean	0.013	1.120	5.248	0.742	0.016	0.128	-6.011	0.484
Median	0.001	1.064	5.134	0.580	0.095	0.060	-4.959	0.479
Min	-0.981	-0.720	0.278	-0.682	-4.572	-0.948	-24.685	0.000
Q1	-0.063	0.653	3.584	0.334	0.002	-0.177	-8.110	0.255
Q3	0.075	1.515	6.817	0.964	0.161	0.329	-2.709	0.709
Max	12.500	3.896	10.188	4.412	2.735	26.066	1.763	1.000
Std. Dev.	0.152	0.742	2.206	0.662	0.573	0.504	4.889	0.270
N	815333	815333	815333	815333	815333	815333	815333	815333

Panel B. Pearson Correlation Coefficients

	RET	***BETA***	***SIZE***	***BM***	***ROE***	***MOM***	DR_{BhSh}	***SYY***
RET	1							
BETA	-0.004**	1						
SIZE	-0.025**	0.094**	1					
BM	0.038**	-0.088**	-0.413**	1				
ROE	0.004**	-0.038**	0.160**	-0.046**	1			
MOM	0.010**	0.030**	0.144**	-0.255**	0.097**	1		
DR_{BhSh}	0.008**	0.136**	-0.356**	0.318**	-0.117**	-0.290**	1	
SYY	-0.035**	0.102**	-0.053**	0.049**	-0.065**	-0.230**	0.273**	1

Table 2
Portfolio Analysis

This table presents the raw and risk-adjusted value-weighted returns (in percentage) of portfolios derived from univariate and double-sorted analysis. Particularly, Panel A presents the raw and risk-adjusted value-weighted returns (derived from five-factor model of Fama and French, 2015) of portfolios formed monthly, based on firms' distress risk (DR_{BhSh}) and mispricing measure (*SYY*) of the previous month. The distress risk measure is estimated similar to Bharath and Shumway (2008) as described in section 3.2 while the mispricing measure is calculated similar to Stambaugh *et al.* (2015). Panel B1 and B2 present the raw and risk-adjusted (derived from five-factor model of Fama and French, 2015) value-weighted returns, respectively, of double-sorted portfolios based on distress effect controlled by *SYY* (our primary mispricing proxy). Portfolios are formed from January of 1976 to December of 2015, when the data are available. Specifically, stocks are sorted into five portfolios based on their mispricing measure of the previous month. Within each mispricing portfolio, stocks are sorted into five portfolios based on their distress risk variables. Highest-Lowest column/row are the return difference between the highest and lowest distress portfolios. *t*-statistics (in parentheses) are derived from Newey-West (1987) adjusted standard errors. * and ** indicate significance at the 5% and 1% level, respectively.

Panel A. Univariate Analysis

	Raw Return		**Risk-Adjusted Return**	
Portfolios	DR_{BhSh}	***SYY***	DR_{BhSh}	***SYY***
1-Lowest	0.95**	1.29**	-0.02	0.18
	(5.40)	(5.56)	(-0.27)	(1.68)
2	1.05	1.23**	0.03	0.22*
	(5.45)	(5.86)	(0.51)	(2.50)
3	0.97**	1.07**	-0.14	0.12
	(4.73)	(5.08)	(-1.81)	(1.61)
4	1.00**	1.04**	-0.19*	0.09
	(4.54)	(4.91)	(-2.12)	(1.15)
5	0.86**	1.05**	-0.37**	0.11
	(3.70)	(4.70)	(-2.73)	(1.21)
6	0.92**	0.86**	-0.27*	-0.18
	(3.60)	(3.68)	(-2.19)	(-1.92)
7	1.01**	0.89**	-0.25	-0.10
	(3.78)	(3.81)	(-1.92)	(-1.15)
8	0.91**	0.92**	-0.42*	-0.12
	(3.17)	(3.52)	(-2.59)	(-1.14)
9	0.92**	0.57**	-0.48*	-0.30**
	(2.77)	(2.07)	(-2.00)	(-2.85)
10-Highest	0.13	0.05	-1.47**	-0.73**
	(0.32)	(0.15)	(-6.46)	(-4.82)
Highest-Lowest	-0.82**	-1.23**	-1.45**	-0.91**
	(-2.70)	(-5.57)	(-5.46)	(-4.19)

Panel B. Double-Sorted Portfolio Analysis: Distress effect controlled by Mispricing (*SYY*)

Panel B1. Raw Returns

		DR_{BhSh}					
		1-Lowest	**2**	**3**	**4**	**5-Highest**	**Highest-Lowest**
	1-Lowest	1.09**	1.18**	1.56**	1.66**	1.92**	0.84**
		(6.08)	(4.87)	(6.60)	(5.87)	(5.36)	(2.65)
	2	1.00**	1.16**	1.16**	1.27**	1.28**	0.28
		(5.08)	(5.27)	(5.26)	(4.57)	(3.49)	(0.93)
SYY	**3**	0.97**	1.07**	0.96**	1.29**	1.12**	0.15
		(4.89)	(4.40)	(3.69)	(4.30)	(3.20)	(0.54)
	4	0.87**	0.97**	0.94**	0.97**	0.75	-0.12
		(4.20)	(3.88)	(3.86)	(3.17)	(1.95)	(-0.42)
	5-Highest	0.69**	0.64*	0.54	0.34	0.03	-0.66*
		(3.44)	(2.33)	(1.76)	(0.99)	(0.08)	(-2.21)

Panel B2. Risk-adjusted Returns

		DR_{BhSh}					
		1	**2**	**3**	**4**	**5-Highest**	**Highest-Lowest**
	1-Lowest	0.41**	0.43**	0.59**	0.44**	0.73**	0.32
		(3.45)	(3.30)	(3.83)	(2.74)	(3.15)	(1.19)
	2	0.40**	0.39**	0.26*	0.24	0.02	-0.39
		(3.63)	(2.73)	(1.96)	(1.67)	(0.07)	(-1.39)
SYY	**3**	0.34**	0.30*	-0.03	0.22	-0.11	-0.45
		(2.94)	(1.99)	(-0.22)	(1.27)	(-0.45)	(-1.64)
	4	0.20	0.14	0.06	-0.12	-0.32	-0.51
		(1.67)	(1.07)	(0.36)	(-0.61)	(-1.09)	(-1.53)
	5-Highest	0.03	-0.07	-0.23	-0.60**	-0.98**	-1.01**
		(0.21)	(-0.41)	(-1.00)	(-2.58)	(-3.53)	(-3.39)

Table 3

Extended Fama and French Type Regressions

This table presents the Fama-MacBeth regressions of Eq. (4). The dependent variable of Eq. (4) is the monthly stock excess returns (*EXRET*) in percentage. *BETA* is estimated over a 3-year period using the CAPM. *SIZE* is the natural logarithm of market value of equity. Book-to-Market ratio is the book value of common equity divided by market value of equity. *ROE* (Return-on-Equity) is equal to net income over book value of common equity. *MOM* (Momentum) is calculated as the cumulative monthly return of the previous 6 months leaving a one-month gap. DR_{BhSh} is the negative distance to default which is estimated similar to Bharath and Shumway (2008) (Eq. 1). *SYY* is the mispricing measure of Stambaugh *et al.* (2015), which is calculated based on a composite anomaly ranking as described in Appendix A1. $DR_{BhSh} \times CAR$ is the interaction term between DR_{BhSh} and *CAR*. All explanatory variables are lagged by one month (*t-1*). Panel A presents the main model specifications, while Panel B presents Model (3) from Panel A based on five mispricing portfolios sorted by *SYY*. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively, using Newey-West (1987) adjusted *t*-statistic (in parentheses).

	Panel A					**Panel B**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(3i) P_1-Lowest**	**(3ii) P_2**	**(3iii) P_3**	**(3iv) P_4**	**(3v) P_5-Highest**
Constant	1.256***	1.109***	1.010**	2.066***	2.337***	2.236***	2.006***	0.866**	0.842*	-0.612
	(3.12)	(2.86)	(2.45)	(4.99)	(5.53)	(4.97)	(4.40)	(2.02)	(1.93)	(-1.32)
BETA	-0.001	-0.000	0.030	0.082	0.086	0.262**	-0.000	0.120	0.056	0.014
	(-0.01)	(-0.00)	(0.34)	(0.94)	(0.99)	(2.44)	(-0.00)	(1.21)	(0.50)	(0.15)
SIZE	-0.112***	-0.125***	-0.140***	-0.131***	-0.129***	-0.231***	-0.214***	-0.079**	-0.087**	-0.031
	(-2.61)	(-3.12)	(-3.60)	(-3.45)	(-3.39)	(-5.28)	(-4.53)	(-2.05)	(-2.05)	(-0.65)
BM	0.342***	0.460***	0.487***	0.430***	0.443***	0.421***	0.362***	0.409***	0.256**	0.787***
	(3.50)	(5.16)	(5.62)	(5.20)	(5.41)	(3.59)	(2.86)	(4.02)	(2.27)	(5.51)
ROE		0.162**	0.150*	0.127	0.134*	0.151	0.388**	0.036	0.270	0.139
		(2.02)	(1.90)	(1.59)	(1.67)	(1.11)	(2.09)	(0.16)	(1.17)	(0.71)
MOM		1.073***	1.016***	0.508**	0.471**	0.371	-0.056	0.671**	0.375	1.194***
		(4.72)	(4.73)	(2.33)	(2.18)	(1.52)	(-0.18)	(2.57)	(1.38)	(4.29)
DR_{BhSh}			-0.022**	0.005	0.053***	0.017*	-0.000	0.002	-0.006	-0.060***
			(-2.44)	(0.55)	(5.84)	(1.87)	(-0.04)	(0.15)	(-0.47)	(-3.61)
SYY				-1.922***	-2.578***					
				(-14.04)	(-16.04)					
$DR_{BhSh} \times SYY$					-0.122***					
					(-8.34)					
Obs.	815333	815333	815333	815333	815333	163256	163071	163065	163070	162871
R-Squared	0.030	0.038	0.040	0.043	0.044	0.062	0.064	0.063	0.062	0.060

Table 4.
The Role of Earnings Management in the Distress Risk Anomaly

This table presents Fama-MacBeth regression coefficients for our base model (5) of Table 3 based on low and high earnings management (EM). This table shows three (3) alternative EM measures: a) the three-year moving sum of total accruals (*ACCR3YR*), b) the three-year moving sum of discretionary accruals (*DACCR3YR*) derived from modified Jones model (Dechow *et al.*, 1995), and c) the three-year moving sum of performance-matched discretionary accruals (*PM_DACCR3YR*) of modified Jones model (Kothari *et al.*, 2005). The definitions of *ACCR3YR, DACCR3YR* and *DACCR3YR* are provided in Appendix A2. *LOW* and *HIGH* refers to the sub-samples of EM measures. *LOW* includes the stocks in the first quintile of EM and *HIGH* the stock in the fifth quintile. All models include constant and control variables, *BETA*, *SIZE*, *BM*, *ROE*, *MOM*. All explanatory variables are lagged by one month (*t-1*). *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively, using Newey-West (1987) adjusted *t*-statistic (in parentheses).

EM Measure:	***ACCR3YR***		***DACCR3YR***		***PM_DACCR3YR***	
Sub-Samples:	**(*LOW*)**	**(*HIGH*)**	**(*LOW*)**	**(*HIGH*)**	**(*LOW*)**	**(*HIGH*)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
DR_{BhSh}	0.048	0.019	0.037	0.108***	0.030	0.121***
	(1.29)	(0.49)	(1.36)	(3.78)	(1.26)	(3.60)
SYY	-2.417***	-2.681***	-1.798***	-2.698***	-1.862***	-2.988***
	(-5.66)	(-7.79)	(-4.30)	(-6.78)	(-4.74)	(-7.77)
$DR_{BhSh} \times SYY$	-0.085	-0.111**	0.003	-0.150***	0.000	-0.212***
	(-1.17)	(-1.99)	(0.05)	(-2.82)	(0.01)	(-3.84)
CONTROLS	YES	YES	YES	YES	YES	YES
Obs.	91397	91052	71958	71604	71599	71265
R-Squared	0.114	0.101	0.119	0.115	0.121	0.112

Table 5.
Double-Sorted Portfolio Analysis – Alternative Measures

This table presents the risk-adjusted value-weighted returns (in percentage) of double-sorted portfolios based on alternative distress and mispricing variables' specifications, which are divided into two panels. Panel A presents the distress risk effect (based on alternative distress risk proxies, DR_{CDLT}, DR_{CHS}) controlled by analysts' disagreement and Panel B shows the results of distress effect controlled by alternative mispricing measures. Portfolios are formed from January of 1976 to December of 2015, when the data are available. Specifically, stocks are sorted into five portfolios based on their mispricing measure of the previous month. Within each mispricing portfolio, stocks are sorted into five portfolios based on their distress risk variables. The table shows results for three (3) mispricing measures: 1) the composite anomaly ranking (*SYY*) of Stambaugh *et al.* (2015), 2) the mispricing measure (*RRV*) of Rhodes-Kropf *et al.* (2005), and 3) the analysts' disagreement (*DIS*), that is equal to the earnings forecasts dispersion. The distress risk proxies are based on Bharath and Shumway (2008), DR_{BhSh} (primary distress risk), Charitou *et al.* (2013), DR_{CDLT} and the failure score of Campbell *et al.* (2008), DR_{CHS}, as described in section 3.2. Highest-Lowest column are the return difference between the highest and lowest distress portfolios. *t*-statistics (in parentheses) are derived from Newey-West (1987) adjusted standard errors. * and ** indicate significance at the 5% and 1% level, respectively.

Panel A. Distress effect (DR_{CDLT} and DR_{CHS}) controlled by Mispricing (*SYY*)

				DR_{CDLT}			
		1-Lowest	**2**	**3**	**4**	**5-Highest**	**Highest-Lowest**
SYY	**1-Lowest**	0.34*	0.43**	0.41**	0.44**	0.40*	0.06
		(2.52)	(3.89)	(2.98)	(3.81)	(2.18)	(0.26)
	2	0.45	0.28*	0.15	0.12	0.04	-0.41
		(3.6)	(2.36)	(1.22)	(0.83)	(0.21)	(-1.79)
	3	0.20	0.36**	0.06	0.11	-0.19	-0.39
		(1.57)	(2.97)	(0.34)	(0.78)	(-0.92)	(-1.71)
	4	0.11	0.18	0.03	-0.21	0.01	-0.09
		(0.78)	(1.24)	(0.16)	(-1.14)	(0.06)	(-0.3)
	5-Highest	0.08	0.03	-0.22	-0.39	-0.77**	-0.85**
		(0.52)	(0.19)	(-1.01)	(-1.65)	(-2.84)	(-2.85)

				DR_{CHS}			
		1-Lowest	**2**	**3**	**4**	**5-Highest**	**Highest-Lowest**
SYY	**1-Lowest**	0.50**	0.51**	0.43**	0.51*	0.60**	0.10
		(2.75)	(4.00)	(3.24)	(2.40)	(2.74)	(0.32)
	2	0.32*	0.27	0.36**	0.54**	0.96**	0.64
		(2.04)	(2.49)	(2.99)	(2.98)	(2.94)	(1.54)
	3	0.31*	0.12	0.03	0.55**	-0.31	-0.62*
		(2.54)	(1.00)	(0.18)	(2.92)	(-1.31)	(-2.35)
	4	0.07	-0.05	0.10	0.08	0.05	-0.02
		(0.55)	(-0.34)	(0.72)	(0.34)	(0.21)	(-0.07)
	5-Highest	-0.03	-0.12	-0.22	-0.52*	-0.95**	-0.92*
		(-0.21)	(-0.6)	(-1.01)	(-2.01)	(-3.04)	(-2.49)

Panel B. Distress effect controlled by alternative mispricing proxies (RRV and DIS)

		DR_{BhSh}					
		1-Lowest	**2**	**3**	**4**	**5-Highest**	**Highest-Lowest**
RRV	**1-Lowest**	0.56**	0.63**	0.34*	0.47*	0.28	-0.28
		(3.64)	(5.05)	(2.23)	(2.54)	(1.07)	(-0.84)
	2	0.48**	0.22	0.39*	0.24	-0.11	-0.58*
		(4.35)	(1.61)	(2.20)	(1.60)	(-0.51)	(-2.51)
	3	0.13	0.53**	0.24	0.14	0.00	-0.13
		(1.15)	(3.15)	(1.84)	(1.00)	(0.00)	(-0.43)
	4	0.44**	0.09	-0.18	-0.30	-0.27	-0.70**
		(4.84)	(0.69)	(-1.29)	(-1.83)	(-1.19)	(-2.77)
	5-Highest	0.41**	0.17	-0.01	-0.02	-0.74**	-1.16**
		(3.61)	(1.48)	(-0.1)	(-0.11)	(-3.34)	(-4.31)
		DR_{BhSh}					
		1-Lowest	**2**	**3**	**4**	**5-Highest**	**Highest-Lowest**
DIS	**1-Lowest**	0.37**	0.38**	0.34*	0.45**	0.20	-0.17
		(3.18)	(3.55)	(2.52)	(3.22)	(1.03)	(-0.71)
	2	0.19	0.19	0.12	0.03	-0.02	-0.21
		(1.73)	(1.63)	(0.81)	(0.21)	(-0.08)	(-0.79)
	3	0.40**	0.34**	0.22	-0.10	-0.03	-0.43
		(2.99)	(2.55)	(1.85)	(-0.61)	(-0.14)	(-1.82)
	4	0.48**	0.18	0.06	-0.08	-0.28	-0.75*
		(3.28)	(0.97)	(0.41)	(-0.46)	(-0.95)	(-2.13)
	5-Highest	0.32	0.00	-0.18	-0.27	-1.13**	-1.45**
		(1.71)	(-0.02)	(-0.99)	(-1.13)	(-3.54)	(-4.11)

Table 6.
Alternative DR and Mispricing Measures

This table provides the robustness Fama-MacBeth regression coefficients for our base model (Model (5) of Table 3) using alternative distress risk and mispricing measures. The alternative distress risk measures are DR_{CDLT} and DR_{CHS} as described in section 3.2. The alternative mispricing measures are *RRV* and *DIS* as described in section 3.2. All models include constant and control variables, *BETA*, *SIZE*, *BM*, *ROE*, *MOM*. All explanatory variables are lagged by one month (*t-1*). *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively, using Newey-West (1987) adjusted *t*-statistic (in parentheses).

	(1)	(2)	(3)	(4)	(5)
DR_{BhSh}	0.057***			-0.015*	-0.014
	(5.56)			(-1.79)	(-1.51)
DR_{CDLT}		0.051***			
		(5.46)			
DR_{CHS}			0.133*		
			(1.93)		
SYY	-2.627***	-2.460***	-5.656***		
	(-16.11)	(-15.75)	(-10.62)		
RRV				-0.550***	
				(-5.31)	
DIS					-0.613***
					(-3.69)
$DR_{BhSh}\times SYY$	-0.131***				
	(-8.62)				
$DR_{CDLT}\times SYY$		-0.112***			
		(-7.76)			
$DR_{CHS}\times SYY$			-0.518***		
			(-7.69)		
$DR_{BhSh}\times RRV$				-0.026**	
				(-2.40)	
$DR_{BhSh}\times DIS$					-0.070**
					(-2.13)
CONTROLS	YES	YES	YES	YES	YES
Obs.	815333	807412	776609	794350	495726
R-Squared	0.044	0.044	0.047	0.044	0.062

Table 7.
Robustness on *DR-Return* Relation

This table provides the robustness Fama-MacBeth regression results based on "pure" distress risk measures (DR^{SYY}_{BhSh}, DR^{SYY}_{CDLT}, DR^{SYY}_{CHS} DR^{RRV}_{BhSh},, DR^{DIS}_{BhSh},) derived from Eq. (5). Models (1) to (3) present the standard *DR* measures while Models (4) to (6) show the "pure" *DR* measures using the mispricing measure of Stambaugh *et al*. (2015), *SYY*, in the decomposition method, Eq. (5). Models (7) and (8) use the alternative mispricing measures (*RRV* and *DIS*) for the decomposition method. All models include constant and control variables, *BETA*, *SIZE*, *BM*, *ROE*, *MOM*. All explanatory variables are lagged by one month (*t-1*). *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively, using Newey-West (1987) adjusted *t*-statistic (in parentheses).

	"*Contaminated*" *DR* Measures			**"*Pure*" *DR* Measures**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
DR_{BhSh}	-0.022**							
	(-2.53)							
DR_{CDLT}		-0.019**						
		(-2.17)						
DR_{CHS}			-0.200***					
			(-3.33)					
DR^{SYY}_{BhSh}				0.010				
				(1.39)				
DR^{SYY}_{CDLT}					0.011			
					(1.57)			
DR^{SYY}_{CHS}						0.020		
						(0.43)		
DR^{RRV}_{BhSh}							-0.009	
							(-1.19)	
DR^{DIS}_{BhSh}								0.004
								(0.56)
CONTROLS	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	465084	465084	465084	465084	465084	465084	465084	465084
R-Squared	0.058	0.058	0.060	0.057	0.057	0.059	0.058	0.057

Appendix A1. Returns Anomalies of Stambaugh *et al.* (2015) mispricing measure (*SYY*)

Our main mispricing measure suggested by Stambaugh *et al.* (2015), *SYY*, relies on 9 asset pricing anomalies. The key variables derived from these anomalies are described below.

1) Net stock issues: Fama and French (2008) show that companies with high net stock issues tend to have lower subsequent returns. Net stock issues are defined as the growth rate of the split-adjusted shares outstanding year-over-year. The measure is estimated in a monthly frequency.

2) Composite equity issues: Daniel and Titman (2006) using the composite equity issuance show that firms that issue shares underperform non-issuer firms. The composite equity issuance is defined as the growth rate of the firm's market capitalization (stock price multiplied by number of shares outstanding) minus the stock return.

3) Total accruals: Firms with high total accruals have lower returns than firms with low total accruals (Sloan, 1996). Total accruals are measured by the following equation:

$$ACCR_{i,q} = \left(\Delta CA_{i,q}\text{-}\Delta Cash_{i,q}\right)\text{-}\left(\Delta CL_{i,q}\text{-}\Delta STD_{i,q}\text{-}\Delta TP_{i,q}\right)\text{-}DEP_{i,q} \qquad \text{(A1.1)}$$

where ΔCA is the change in current assets (Compustat item "act"), $\Delta Cash$ is the change in cash/cash equivalents (Compustat item "che"), ΔCL is the change in current liabilities (Compustat item "lct"), ΔSTD is the change in debt included in current liabilities (Compustat item "dlc"), ΔTP is the change in income taxes payable (Compustat item "txp"), and DEP is the depreciation and amortization expense (Compustat item "dp"). Subsequently, total accruals ($ACCR_{i,q}$) are scaled by previous year total assets.

4) Net operating assets: Stocks with high net operating assets tend to have lower returns (Hirshleifer *et al.*, 2004). Net operating assets is equal to operating assets minus operating liabilities. Operating assets are defined as total assets minus cash and short-term investment (Compustat item "che"). Operating liabilities are calculated as total assets minus short-term debt

(Compustat item “dlc”) minus long-term debt (Compustat item “dltt”) minus minority interest (Compustat item “mib”) minus preferred stock (Compustat item “pstk”) minus common stocks (Compustat item “ceq”).

5) Gross profitability: Novy-Marx (2013) finds that profitable firms as defined by gross profitability measure tend to have higher returns than non-profitable firms. Gross profitability is calculated as total revenues (Compustat item “revt”) minus cost of goods sold (Compustat item “cogs”) scaled by total assets (at).

6) Asset growth: Cooper *et al*. (2008) document a strong negative relation between firm’s asset growth and subsequent (abnormal) return. Asset growth is measured as the percentage change of the firm’s asset in the previous year. This measure is estimated year-over-year using quarterly data.

7) Momentum: Momentum anomaly is one of the most widely accepted anomaly in asset pricing, firstly discovered by Jegadeesh and Titman (1993). Jegadeesh and Titman (1993) show that stocks high (low) past returns tend to have high (low) future returns. The momentum variable in this study is estimated as the cumulative returns from month at t-6 to month at t-2.

8) Return on assets: Fama and French (2006) show that firms with higher return on assets have higher expected returns than firms with lower return on asset. Return on assets is defined as the ratio of quarterly earnings (Compustat item “ni”) over the last quarter’s total assets.

9) Investment to assets: Prior studies (Titman, Wei, & Xie, 2004; Xing, 2008) show that firms with higher investment activity have lower returns than firms with lower past investment. Investment to assets is measured as the as the annual change in gross property, plant, and equipment (Compustat item “ppent”), plus the annual change in inventories (Compustat item “invt”), scaled by total assets (Lyandres *et al.*, 2008, Wu, Zhang, and Zhang, 2010).

Appendix A2. Univariate Analysis of Alternative Distress and Mispricing Measures

Table A1 presents the portfolio analysis based on alternative distress and mispricing measures used in this study. The risk-adjusted return difference between highest and lowest alternative distress risk measures, DR_{CDLT} and DR_{CHS}, is negative (-0.86% and -0.73) and significant for 1% significant level consistent with the findings of our main distress risk measure. The risk-adjusted return difference between highest and lowest mispricing portfolios for the two measures is negative and statistically significant for 1% significant level consistent with the findings of our main mispricing measures. Overall, the results show that stocks with lower mispricing (probably undervalued stocks) and lower distress risk perform better than high mispricing stocks (overvalued stocks) and high distressed stocks, respectively.

Table A2
Portfolio Analysis - Alternative Mispricing and Distress Risk Measures

This table presents the risk-adjusted value-weighted returns (in percentage) of single-sorted portfolios derived from alternative distress and mispricing measures. Particularly, the results illustrate the risk-adjusted returns of portfolios formed monthly, based on firms' alternative distress risk (DR_{CDLT} and DR_{CHS}) and mispricing variables (*RRV* and *DIS*) of the previous month. Portfolios are formed from January of 1976 to December of 2015, when the data are available. The alternative distress risk measures are based on Charitou *et al.* (2013), DR_{CDLT} and the failure probability score of Campbell *et al.* (2008), as described in section 3.2. The mispricing variables are *RRV* that is derived from the decomposition approach of *M/B* ratio developed by of Rhodes-Kropf *et al.* (2005) and the dispersion of analyst' expectations, *DIS*. Highest-Lowest row is the return difference between the highest and lowest mispricing (variables) portfolios. *t*-statistics (in parentheses) are derived from Newey-West (1987) adjusted standard errors. * and ** indicate significance at the 5% and 1% level, respectively.

	Risk-Adjusted Returns			
Portfolios	DR_{CDLT}	DR_{CHS}	***RRV***	***DIS***
1-Lowest	-0.05	0.30*	0.39*	0.34**
	(-0.66)	(2.14)	(2.52)	(3.27)
2	-0.03	0.07	0.19	-0.13
	(-0.46)	(1.09)	(1.60)	(-1.89)
3	-0.10	-0.05	0.14	-0.01
	(-1.23)	(-0.73)	(1.41)	(-0.09)
4	-0.08	-0.09	0.07	0.01
	(-0.92)	(-1.07)	(0.57)	(0.12)
5	-0.32*	-0.09	-0.04	0.03
	(-2.24)	(-1.01)	(-0.55)	(0.45)
6	-0.26*	0.09	-0.27**	0.10
	(-2.43)	(0.67)	(-3.31)	(0.93)
7	-0.30*	-0.35*	-0.18*	-0.03
	(-2.11)	(-2.24)	(-2.17)	(-0.24)
8	-0.47**	-0.42*	-0.25**	-0.03
	(-3.15)	(-2.37)	(-3.48)	(-0.21)
9	-0.32	-0.79**	-0.45**	-0.23
	(-1.43)	(-3.42)	(-4.79)	(-1.89)
10-Highest	-1.36**	-0.91**	-0.15	-0.20
	(-5.98)	(-3.51)	(-1.56)	(-1.29)
Highest-Lowest	-1.31**	-1.21**	-0.54**	-0.54**
	(-4.93)	(-3.74)	(-2.88)	(-2.66)

Appendix A3. Earnings Management Measures

This Appendix presents the estimation of the three earnings management measures tested in this study. The first measure is based on total accruals of Sloan (1996). Total accruals are defined by Eq. (A1.1). Similar to Hutton *et al.* (2009), we estimate the three-year moving sum of total accruals, *ACCR3YR*. Firms that have consistently large values of accruals are more likely to engage into earnings management practices. Because total accruals may not be the most appropriate measure to capture earnings management due to managerial discretion our next two earnings management measures are based on discretionary accruals.

The first *discretionary accruals* measure is derived from the *modified Jones model* (Dechow *et al.*, 1995). To define discretionary accruals through the modified Jones model, firstly, we estimate the following cross-sectional regression equation using 48-industry classification scheme of Fama and French (1997) for each fiscal quarter:

$$\frac{ACCR_{i,q}}{TA_{i,q-4}} = a_0 \frac{1}{TA_{i,q-4}} + \beta_1 \frac{\Delta SALES_{i,q}}{TA_{i,q-4}} + \beta_2 \frac{PPE_{i,q}}{TA_{i,q-4}} \tag{A3.1}$$

where $ACCR_{i,q}$ is the total accruals defined by Eq. (A1.1) for firm *i* at quarter *q*, $TA_{i,q-4}$ is the total assets for firm *i* at the previous year (*i.e.* before 4 quarters). $\Delta SALES_{i,q}$ is the change of sales in quarter *q* minus the revenues in quarter *q-4*. $PPE_{i,q}$ is the gross property plant and equipment in quarter *q*. Discretionary quarterly accruals scaled by lagged total assets for firm *i* at quarter *q* is derived from of the following equation:

$$DACCR_{i,q} = \frac{ACCR_{i,q}}{TA_{i,q-4}} - \left(\hat{a}_0 \frac{1}{TA_{i,q-4}} + \hat{\beta}_1 \frac{\Delta SALES_{i,q} - \Delta REC_{i,q}}{TA_{i,q-4}} + \hat{\beta}_2 \frac{PPE_{i,q}}{TA_{i,q-4}}\right) \tag{A3.2}$$

where $\Delta REC_{i,q}$ is the change of total receivables for firm *i* at quarter *q* which represents the modification of Jones (1991) model. $\hat{a}_0$, $\hat{\beta}_1$, $\hat{\beta}_2$ are the estimated coeficients from Eq. (A3.1) of Dechow *et al.* (1995). Then we proceed to the estimation of the three-year (12 quarters) moving sum of $DACCR_{i,q}$, namely *DACCR3YR*.

The second discretionary accruals measure is based on the performance-matched discretionary accruals measure of Kothari *et al.* (2005). This measure is estimated in the same manner as the modified Jones model but augmented to include return on assets in Eq. (A3.1) and (A3.2). Therefore, Eq. (A3.1) and (A3.2) are transformed as follow:

$$\frac{ACCR_{i,q}}{TA_{i,q-4}} = a_0 \frac{1}{TA_{i,q-4}} + \beta_1 \frac{\Delta SALES_{i,q}}{TA_{i,q-4}} + \beta_2 \frac{PPE_{i,q}}{TA_{i,q-4}} + \beta_3 \frac{ROA_{i,q}}{TA_{i,q-4}} \tag{A3.1a}$$

$$PM\_DACCR_{i,q} = \frac{ACCR_{i,q}}{TA_{i,q-4}} - \left(\hat{a}_0 \frac{1}{TA_{i,q-4}} + \hat{\beta}_1 \frac{\Delta SALES_{i,q} - \Delta REC_{i,q}}{TA_{i,q-4}} + \hat{\beta}_2 \frac{PPE_{i,q}}{TA_{i,q-4}} + \hat{\beta}_3 ROA_{i,q} \right) \tag{A3.3}$$

where $ROA_{i,q}$ is the return on assets for firm *i* at quarter *q* estimated as net income divided by total assets. After the estimation of $PM\_DACCR_{i,q}$ we proceed to the calculation of the three-year (12 quarters) rolling summation of the performance-matched discretionary accruals, *PM_DACCR3YR*.