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Predicting financial distress: The role of earnings quality

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Predicting financial distress:

The role of earnings quality

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by

Ruihao Ke

2012

Abstract of the Dissertation

Predicting financial distress:
The in debt contracting

by

Ruihao Ke
Doctor of Philosophy in Management
University of California, Los Angeles, 2012
Professor Brett Trueman, Chair

Abstract

This study investigates the role of earnings quality (EQ) in the prediction of financial distress. Specifically, I predict and find that EQ is positively associated with the informativeness of both accounting- and price-based distress predictors, and negatively associated with distress risk, itself. These results hold across several EQ measures and various distress prediction models, and are driven by both components of EQ measures – that related to firm fundamentals and that related to managerial discretion. Furthermore, I find that incorporating the impact of EQ improves prediction models' out-of-sample performance, especially when the forecast horizon is longer than one year. These results contribute to the literature by documenting that EQ impacts the prediction of financial distress, the most crucial input in the lending process.

The dissertation of Ruihao Ke is approved.

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University of California, Los Angeles

2012

To my wife, my parents, and my advisors whose continuous support made my research possible.

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VITA

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1. Introduction

Understanding the implications of earnings quality (EQ) for the functioning of capital markets has been the focus of a substantial amount of accounting research, as researchers contend that EQ affects the amount of financial information available to market participants. Recent studies have provided a significant body of evidence suggesting that EQ influences the functioning of debt markets, notably through its impact on the contracting use of accounting information (Bharath et al. 2008). However, its impact on the predictive use of accounting information is less well understood. To shed light on this issue, I investigate how EQ influences the prediction of financial distress where accounting information plays an important role.

I consider two possible channels by which EQ can influence distress prediction. The first is an indirect channel, whereby EQ influences the informativeness of variables serving as distress predictors. This channel implies that measures of EQ can be used as a conditioning variable for the extant predictors in distress prediction models. Motivated by the prior literature that finds EQ to be associated with the informativeness of financial information in equity markets, I conjecture that EQ will be positively associated with the informativeness of extant distress predictors.[1]

The second channel by which EQ could influence distress prediction is through its direct association with distress risk. This implies that measures of EQ should be used as an independent predictor in distress prediction models. I conjecture that low EQ is associated with high distress risk. This prediction builds on two important findings in the literature. The first is that low EQ is associated with more volatile operating environments, as captured by firm fundamentals such as size, cash flow volatility, and sales volatility (Dechow and Dichev 2002; Francis et al. 2005). To

[1] For a review of the empirical evidence on how EQ impacts the informativeness of financial information in equity markets, see Francis et al. (2006) and Dechow et al. (2010).

the extent that these firm fundamentals are associated with distress risk, EQ measures would have predictive ability for distress. The second finding is that firms tend to manage earnings, thereby likely to be of low EQ, prior to covenant violations (DeFond and Jiambalvo 1994; Sweeney 1994). Since these violations can be considered as an early sign of distress, we might observe an association between low EQ and high distress risk.[2]

I test my predictions by applying them to three widely-used distress prediction models: Altman (1968), Ohlson (1980), and, more recently, Bharath and Shumway (2008).[3] Specifically, to test the conjecture that EQ impacts the informativeness of distress predictors, I interact EQ measures with accounting- and price-based predictors in the prediction models; to test the conjecture that EQ is directly associated with distress risk, I add EQ measures as independent predictive variables to the models. Then I estimate the coefficients of these expanded prediction models using the data from 1985 to 2010 and defining distress events as defaults, performance-related delistings, and bankruptcies.[4]

My analyses generate several sets of results. The first set shows that EQ is associated with the informativeness of both the accounting- and price-based distress predictors; these predictors are less informative of financial distress in low EQ firms than they are in high EQ firms. The second set of results shows that EQ, itself, is associated with distress risk; low EQ firms are significantly more likely to experience financial distress than are high EQ firms after controlling for predictors used in the prediction models. Both sets of results are robust to the EQ

[2] Managers also manage earnings to beat analyst forecasts and to increase their bonus. To the extent that these are important reasons to manage earnings, they could reduce the association between earnings quality and distress risk.

[3] The Altman and Ohlson models employ accounting-based predictors, while the Bharath and Shumway (BS) model employs a combination of accounting- and priced-based predictors. My results hold when I use a pure price-based model, the Merton (1974) Distance to Default model.

[4] There is no general consensus on the definition of financial distress. The broad definition adopted in this study is consistent with that in Campbell at al. (2008). My main results would be little changed if I define distress as bankruptcies only.

measures and prediction models employed, as well as to the forecasting horizon over which distress risk is estimated.

To further identify the drivers of my results, I decompose each EQ measure into two components, using the methodology introduced by Francis et al. (2005). One captures the firms' business fundamentals and the other captures managerial discretion. I then expand my prediction models with these components, treating each component as an independent EQ measure. I find that both components of EQ are associated with the informativeness of the predictors, indicating that firm fundamentals, as well as managerial discretion, play an important role in determining the informativeness of distress predictors. Moreover, both components are significantly associated with distress risk, although the association between the fundamental component and distress risk is much stronger than that between the discretionary component and distress risk.

Finally, I examine whether incorporating the impact of EQ improves the out-of-sample prediction of financial distress. The results here are mixed. Some, but not all, EQ measures improve the out-of-sample performance of the prediction models. The magnitude of the improvement varies across different models, but the improvement tends to become stronger as the forecast horizon expands. The weaker results from out-of-sample analyses are not surprising. Coefficient estimates tend to be less precise, because of the holding out portions of the data in estimating model coefficients. Furthermore, firms rarely enter distress, making it difficult to detect statistical significance.

My study makes several contributions to the literature. It is one of the first to provide direct evidence that EQ is associated with the predictive role of accounting information used in the debt market. Moreover, in their recent survey, Dechow et al. (2010) observe that the prior literature emphasizes the role of managerial discretion in determining EQ, but has not paid enough attention to whether and how firm fundamentals impact EQ. My study deepens our understanding on this issue by analyzing how each component of EQ impacts distress prediction.

Most importantly, to the best of my knowledge, my study is the first to show that EQ is related to distress risk, even after controlling for extant distress predictors. This finding provides a new angle to interpret the documented association between EQ and the characteristics of debt contracts. For example, Francis et al. (2005) and Bharath et al. (2008) find that compared to firms with high EQ, those with low EQ tend to choose private, rather than public, debt and to pay a higher interest rate. They attribute these findings to the information asymmetry associated with EQ and suggest that the higher interest rate is consistent with a form of "information risk premium". My finding that EQ is directly associated with distress risk suggests an alternative explanation. Low EQ firms might choose private debt in order to reduce the expected deadweight costs associated with distress, such as restructuring costs. Consequently, they would be inclined to pay a higher interest rate to compensate creditors for bearing higher distress risk.

An obvious implication of my results is that when determining whether the association between EQ and debt contracts is driven by information quality, researchers should control for the distress risk directly associated with EQ. Specifically, instead of using the Altman Z-score or the Ohlson O-score, researchers should use the adjusted versions of these scores, generated by the expanded Altman or Ohlson model that adds EQ measures as independent distress predictors. The adjusted scores incorporate the distress risk associate with EQ measures, and when used as risk controls, can help researchers differentiate information-based from distress risk-based explanations for the association between EQ and debt contracts.

The rest of the paper proceeds as follows. Section 2 reviews the literature and develops my hypotheses. Data selection and research design are described in Section 3. Sections 4 and 5 present the empirical analyses. Section 6 summarizes and concludes.

2. Literature Review and Hypothesis Development

I begin this section by reviewing two independent lines of research: Section 2.1 reviews the literature on EQ and Section 2.2 reviews the literature on distress prediction. Then I develop my hypotheses in Section 2.3.

2.1. Earnings Quality

Understanding EQ's determinants and its economic impact has been of considerable interest to accounting researchers. Since EQ is unobservable, researchers have designed numerous measures for it. Early studies mostly focus on earnings management, proxied by accruals and abnormal accruals (Healy 1985; Jones 1991; Dechow et al. 1995). In the context of EQ studies, researchers usually use the *absolute value* of abnormal accruals. The intuition is that the accruals component of earnings represents a managerial estimate and the bigger the magnitude of the estimate, the more likely it contains intentional or unintentional estimation errors.

More recently, Dechow and Dichev (2002) develop a different type of EQ measure. Their proxy is based on the idea that high quality earnings should map closely to past, current, and future cash flows. They use the *standard deviation* of residual accruals that cannot be explained by realized cash flows as the proxy for accrual quality. A high standard deviation indicates low EQ because it is harder for financial statement users to back out accruals' implications for cash flows.

One drawback of the Dechow and Dichev accrual quality measure is its strict data requirement that limits sample size. One way to mitigate this problem is to use a revised version of accrual quality developed by Francis et al. (2005) which utilizes industry information. Another way, proposed by Dechow and Dichev, is to use instrumental variables for accrual quality, such as earnings volatility. Dichev and Tang (2009) find that earnings volatility is also associated with earnings predictability, another aspect of EQ.

Based on their measure, Dechow and Dichev (2002) examine the determinants of EQ. They find that accrual quality is not only determined by managerial discretion, but is also strongly associated with firm fundamentals, such as size, cash flow volatility, and incidence of losses. Building on this idea, Francis et al. (2005) develop a procedure to separate accrual quality into two components, an innate component that captures EQ due to a firms' business model and operational risk, and a discretionary component that captures EQ due to managerial reporting incentives. However, there is limited further evidence on how each of these two components contributes to the overall impact of EQ (Dechow et al. 2010).

With these EQ measures at hands, researchers have studied how EQ influences the functioning of capital markets, equity markets in particular. For example, measures of EQ are associated with the predictability of future earnings, (Dichev and Tang 2009) the magnitude of price reactions to earnings announcements (Collins and Kothari 1989; Easton and Zmijewski 1989), the level of informed trading (Aboody et al. 2005, Ecker et al. 2006), and stock return volatility (Rajgopal and Venkatachalam 2010).

More recently, accounting researchers have examined whether EQ influences the functioning of debt markets. Francis et al. (2005) show that firms with low EQ on average have higher interest expense than those with high EQ. Bharath et al. (2008) expand Francis et al. (2005) and find that firms with lower EQ tend to choose private, rather than public, debt. Further, the debt they borrow is usually with shorter maturity and bears a higher interest rate. Both Francis et al. (2005) and Bharath et al. (2008) interpret their results from an information risk perspective. In particular, Bharath et al. argue that the low EQ firms choose private debt to reduce transaction costs associated with information asymmetry and then pay a higher interest rate as a form of information risk premium.

2.2. Distress Prediction Models

Since the seminal studies of Beaver (1967) and Altman (1968), researchers have developed numerous models to predict financial distress. This subsection reviews four of the most popular ones: the Altman model and the Ohlson (1980) model which are accounting-based; the Merton (1974) distance-to-default (DD) model which is price-based; and the Bharath and Shumway (2008) model which uses both accounting-based and price-based predictors.

The Altman model is one of the earliest distress prediction models. It chooses five financial ratios to predict distress, as follows:

$$\Pr(Distress = 1) = \mathrm{F}(WC/TA, RE/TA, ROA, Ve/TL, S/TA)$$

where the *Distress* indicator variable equals 1 if the firm experiences distress over the forecast horizon and 0 otherwise, *WC*/*TA* is working capital divided by total assets, *RE*/*TA* is retained earnings divided by total assets, *ROA* is earnings before interest and taxes divided by total assets, *Ve*/*TL* is market value of equity divided by total liabilities, *S*/*TA* is sales divided by total assets.[5]

[5] The details of the variables used in these models can be found in the Appendix.

The Ohlson model is expands the Altman model and uses nine financial ratios to predict distress as follows:

$$\Pr(Distress = 1) = \mathrm{F}(Size, TL/TA, WC/TA, CL/CA, ROA, FU/TL, INTWO, OENEG, CHIN)$$

where *Size* is the log of total assets adjusted by the level of gross national product (GNP), *TL*/*TA* is total liabilities divided by total assets, *CL*/*CA* is current liabilities divided by current assets, *ROA* is net income divided by total assets, *FU*/*TL* is funds provided by operations divided by total liabilities, *INTWO* is an indicator for negative earnings over the last two years, *OENEG* is an indicator for negative book value, and *CHIN* measures change in earnings.[6]

The third model, Merton DD model, is purely price-based and relies on a single variable, implied distress risk, to predict financial distress. The variable, denoted by π^{Merton}, is based on the framework developed by Merton (1974), in which a firm's equity is considered to be a call option on the underlying value of the firm, with strike price equal to the face value of the firm's debt.[7] It is calculated by the following formula.

$$\pi^{Merton} = \mathrm{N}(-DD)$$

$$\text{and } DD = \frac{\ln[(MV(Equity) + Debt)/Debt] + (\mu - 0.5 \cdot \sigma_v^2) \cdot T}{\sigma_v \cdot \sqrt{T}}$$

where N(·) is the cumulative density function for the normal distribution, and *DD*, distance to default, is the difference between the estimated market value of the firm, *MV*(*Equity*)+*Debt*, and the face value of the firm's debt, scaled by an estimated volatility of the firm's asset value, σ_v,

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[6] The definitions of *ROA* in the Altman and Ohlson models are different. For convenience, I refer to both as *ROA*.

[7] Technically, the implied risk measures the probability that a firm will go *bankrupt* by the end of a certain period of time. However, many studies use this implied risk to predict a broader class of financial distress, including events like defaults and performance-related delistings (Bharath and Shumway [2008], Campbell et al. [2008]).

and forecasting horizon, T, with an adjustment for the expected return of the firm, μ. Intuitively, the distress risk is the probability that the value of the firms will be less than the face value of debt by the end of the forecasting horizon.

Researchers have applied various approaches to estimate the unobservable μ and σ_v. One simple approach to estimate σ_v, developed by Bharath and Shumway (2008), is to use a weighted average of past return volatility, as follows:[8]

$$\sigma_v = \frac{MV(Equity)}{MV(Equity)+Debt}\cdot\sigma_{ret,t-1} + \frac{Debt}{MV(Equity)+Debt}\cdot(0.05+0.25\cdot\sigma_{ret,t-1})$$

where $\sigma_{ret,t\text{-}1}$ is the past return volatility, a proxy for the volatility of equity value; $0.05+0.25\cdot\sigma_{ret,t\text{-}1}$ is a proxy for the volatility of debt value.

The Bharath and Shumway model, developed by Bharath and Shumway (2008, Model 7 in Table 3), combines price-based information and accounting-based information to predict financial distress. It takes the following form:

$$\Pr(Distress=1)=\mathrm{F}(\pi^{Merton},\mathrm{Ln}(MVE),\mathrm{Ln}(Debt),\sigma_{ret}^{-1},ExRet,ROA)$$

where π^{Merton} is the implied distress risk discussed above, Ln(MVE) is the log of the market value of equity, Ln($Debt$) is the log of the book value of Debt, σ_{ret}^{-1} is the inverse of annualized stock return volatility, *ExRet* is the return of the firm in excess of the market, and *ROA* is the return on total assets. This model has been shown to outperform the well-known Merton (1974) Distance to Default model.

[8] Other approaches rely on past return volatility to calculate asset volatility as well, for example, Hillegeist et al. (2004).

2.3. Hypotheses Development

As discussed previously, financial distress models can be broadly classified into two categories: accounting-based and price-based. Since previous studies have shown that EQ influences the informativeness of financial information in equity markets, in the context of my setting it is likely to influence the predictive power of accounting-based predictors used in various prediction models. Given that EQ measures are more directly associated with the informativeness of earnings, my study focuses on the two earnings-based variables, namely return on assets (*ROA*) and change in earnings (*CHIN*).[9] My first hypothesis, stated in the alternative, is:

H1a: Return on assets and change in earnings are more informative of financial distress when EQ is high than when it is low.

Not only can EQ influence the predictors in the accounting-based models, it might also influence the most important predictor in the price-based models, implied risk (π^{Merton}). Recall that the most crucial input to calculate π^{Merton} is return volatility, a proxy for the volatility of equity value. I hypothesize that when EQ is low, return volatility tends to become a noisy proxy for the volatility of equity value, therefore, reduces the informativeness of π^{Merton}. This hypothesis is based on two empirical findings. First, low EQ firms tend to have higher information asymmetry and therefore attract more informed trading in the equity markets (Aboody et al. 2005; Ecker et al. 2006). Second, informed trading is likely to increase stock

[9] I also examine the associations between EQ and the informativeness of balance sheet ratios such as debt to total assets, net working capital over total assets, and retained earnings over total assets. I find that most associations are consistent with hypothesis H1a. However, these associations become insignificant once I control for the association between EQ and *ROA*. This result suggests that the association between EQ and the informativeness of *ROA* subsumes the association between EQ and the informativeness of other balance sheet ratios.

return volatility (Frech and Roll 1986; Rajgopal and Venkatachalam 2010). As a result, return volatility associated with low EQ might be a noisy proxy for the volatility of equity value and therefore reduces the predictive power of π^{Merton}. This discussion leads to the hypothesis below, stated in the alternative:

H1b: Implied distress risk, π^{Merton}, is more informative of financial distress when EQ is high than when it is low.

As mentioned in the introduction, the level of EQ, itself, could be directly associated with distress risk. There are two avenues by which this could happen. One is through its association with firm fundamentals that are related to distress risk, such as firm size, cash flow volatility, and incidence of losses. The other avenue is managerial discretion. Studies have found that firms manage their earnings, thereby likely to have low EQ, prior to covenant violations. Since covenant violations can be considered as an early sign of distress, low EQ might be associated with high distress risk. This leads to the following hypothesis, stated in the alternative:

H2: The level of EQ is negatively associated with financial distress risk.

3. Research Design

3.1. Defining Financial Distress

There is no general agreement on the definition of financial distress. Some studies define distress as bankruptcies (Altman 1968), while others define distress as defaults (Bharath and Shumway 2008). Following Campbell et al. (2008), I adopt a broad definition of distress, and consider a firm as distressed if it files for bankruptcy, receives a D level credit rating as a result of defaults on its loans or bonds, or is delisted for performance-related reasons.[10] A firm is regarded as having survived otherwise. Consistent with the prior literature, a firm is eliminated from my sample after its first incidence of distress.

3.2. Earnings Quality Proxies

I use three EQ proxies in this study: the absolute value of abnormal accruals, |*Acc*|, the accrual quality (as in Francis et al. 2005), *AQ*, and the volatility of seasonally adjusted earnings, *Vol*(*ΔE*).

To calculate abnormal accruals, I run the following cross-sectional regression for each of the Fama-French 48 industries with at least 20 firms every year (as in Francis et al. 2005):

$$\frac{TA_{i,t}}{Asset_{i,t-1}} = k_1 \cdot \frac{1}{Asset_{i,t-1}} + k_2 \cdot \frac{(\Delta Rev_{i,t} - \Delta AR_{i,t})}{Asset_{i,t-1}} + k_3 \cdot \frac{PPE_{i,t}}{Asset_{i,t-1}} + \varepsilon_{i,t}$$

where $TA_{i,t}$ is firm *i*'s total accruals in year *t*, calculated as $TA_{it} = (\Delta CA_{i,t} - \Delta CL_{i,t} - \Delta Cash_{i,t} + \Delta STDEBT_{i,t} - DEPN_{i,t})$, in which $\Delta CA_{i,t}$ is firm *i*'s change in current assets (COMPUSTAT item *act*) from year $t - 1$ to year *t*, $\Delta CL_{i,t}$ is firm *i*'s change in current liabilities (*lct*) from year $t - 1$ to year *t*, $\Delta Cash_{i,t}$ is firm *i*'s change in cash (*che*) from year $t - 1$ to year *t*, $\Delta STDEBT_{i,t}$ is firm *i*'s change in debt within current liabilities (*dlc*) from year $t - 1$ to year *t*, $DEPN_{i,t}$ is firm *i*'s depreciation and amortization expense (*dp*) during year *t*; $Asset_{i,t-1}$ is firm *i*'s total assets at the end of year $t - 1$ (*at*); $\Delta Rev_{i,t}$ is firm *i*'s change in sales (*sale*) from year $t - 1$ to year *t*; $\Delta AR_{i,t}$ is firm *i*'s change in accounts receivables (*rect*) from year $t - 1$ to year *t*; $PPE_{i,t}$ is firm *i*'s gross

[10] If I define financial distress as bankruptcies only, results in Section 4 and Section 5.1 would not change. However, the results from out-of-sample tests in Section 5.2 would become weaker, potentially because the limited number of bankruptcies in my sample reduces the power of the tests.

value of property, plant, and equipment (*ppegt*) at the end of year t.[11] All the variables are winsorized at the 1 and 99 percentiles. The regression generates firm- and year-specific residuals which represent the abnormal accruals, $|Acc|$. Higher $|Acc|$ indicates lower EQ.

The second EQ proxy is accrual quality, *AQ*, developed by Dechow and Dichev (2002) and modified by Francis et al. (2005). The intuition behind this proxy is that high-quality working-capital accruals should correlate well with realized operating cash flows. To calculate *AQ*, I first run the following regression each year for each of the Fama-French 48 industries with at least 20 firms in that year.

$$\frac{TCA_{i,t}}{Asset_{i,t-1}} = \phi_0 + \phi_1 \cdot \frac{CFO_{i,t-1}}{Asset_{i,t-1}} + \phi_2 \cdot \frac{CFO_{i,t}}{Asset_{i,t-1}} + \phi_3 \cdot \frac{CFO_{i,t+1}}{Asset_{i,t-1}} + \phi_4 \cdot \Delta Rev_{i,t} + \phi_5 \cdot PPE_{i,t} + \varepsilon_{i,t}$$

where $TCA_{i,t}$ is firm i's total current accruals in year t, calculated as $TCA_{i,t} = (\Delta CA_{i,t} - \Delta CL_{i,t} - \Delta Cash_{i,t} + \Delta STDEBT_{i,t})$; $CFO_{i,t}$ is firm i's cash flow from operations in year t, calculated as $CFO_{i,t} = NIBE_{i,t} - TA_{i,t}$, $NIBE_{i,t}$ is firm i's net income before extraordinary items (*ib*), $TA_{i,t}$ is firm i's total accruals in year t. All the variables are winsorized at the 1 and 99 percentiles.

This procedure generates firm- and year- specific residuals. $AQ_{i,t}$ is the *standard deviation* of firm i's residuals, calculated from year $t-4$ to t. Higher standard deviations indicate lower EQ. Since the estimation procedure of *AQ* utilizes future cash flow information, I use the *lagged* proxy in the prediction models to make sure that this variable does not contain information that is not available to the market at the forecast date.

The third EQ proxy is the volatility of seasonally adjusted earnings, $Vol(\Delta E)$. This proxy is motivated by the findings that earnings volatility is strongly associated with earnings

[11] Results would remain unchanged if I use the modified Jones (1991) model to generate abnormal accruals.

persistence and predictability (Dichev and Tang 2009). Unlike the volatility of earnings, the volatility of seasonally adjusted earnings is likely to classify firms that grow persistently as stable firms.[12] This measure is calculated as follows:

$$Vol(\Delta E)_{i,t} = \sigma\left(\frac{NIBE_{i,t} - NIBE_{i,t-4}}{Total\ Assets_{i,t}}\right)$$

where $NIBE_{i,t}$ is firm i's net income before extraordinary items (*ib*) during quarter t. I use up to 3 years of quarterly earnings with no fewer than 8 observations to calculate this proxy. Again, high volatility indicates low EQ.

3.3. Estimating and Expanding Distress Prediction Models

Table 1, Panel A presents summary statistics for the conservative variables. My statistics are consistent with prior studies. For example, Beatty et al. (2008) report means of 1.25 for skewness and 0.02 for non-operating accruals; my sample reports 1.38 and 0.02, respectively. Callen et al. (2010) report a mean of 0.146 and a median of 0.008 for c-score; my sample reports a mean of 0.10 and a median of 0.02 for the same variable. Also, asymmetric timeliness capture by the Basu measure has the first quartile negative in accord with prior research. Panel A also presents summary statistics for management incentives. The distribution of vega, delta, and the fraction of managerial ownership are similar to those reported by Coles et al. (2006) and Brockman et al., (2010). The statistics reveal skewness in the compensation data since the medians are lower than the means. The mean change in the option portfolio due to a 1% change in the stock volatility is $142.75 (000) while the mean sensitivity to stock prices is $699.07 (000). To test my hypotheses, I expand and estimate three distress prediction models reviewed in

[12] Using the volatility of annual earnings generates the results that are quantatively similar to those based on *Vol*(*ΔE*).

Section 2.2: the Altman model, the Ohlson model, and the Bharath and Shumway model.[13] A summary of the variables used in these models appears in the Appendix.

Following Shumway (2001), Hillegeist et al. (2004), and Campbell et al. (2008), I estimate those prediction models using a logit form. Shumway (2001) demonstrates econometrically that the dynamic logit model uses more information in the data than do single period models and generates consistent estimates.[14] When estimating the model coefficients, the marginal distress probability is assumed to follow a logistic distribution:

$$\Pr_{i,t}(Distress_{i,t+1}=1)=\{1+\exp(-1\cdot(\alpha+\beta\cdot X_{i,t}))\}^{-1}$$

where the *Distress* indicator variable equals 1 if the firm experiences distress over the forecast horizon and 0 otherwise, and *X* is a vector of predictors used in the model and available at the forecast date. In this study, the forecast date for each firm is assumed to be the end of three months after the fiscal year end, when financial statements are assumed to be available to the public.

To incorporate the impact of EQ into the prediction models, I first sort my sample firms into three EQ groups each year, based on the proxies used.[15] Then each group is given an indicator variable. To test the hypothesis that EQ is associated with the informativeness of distress predictors, I interact these indicator variables with the predictors that are hypothesized in H1a and H1b to be influenced by EQ – return on assets (*ROA*), change in earnings (*CHIN*) and

[13] My results hold for the Merton Distance-to-Default model as well.
[14] For more technical details, see Shumway (2001).
[15] Using the portfolio approach can reduce the noise introduced when calculating the EQ measures. My main results are not sensitive to the use of 2, 3, 4, or 5 groups.

implied risk (π^{Merton}) – depending on the model.[16] To test the hypothesis that EQ reflects distress risk, I further add these indicator variables to the original models as independent predictors.

Take the Altman model as an example. Its expanded model takes the following form:

$$\Pr_{i,t}(Distress_{i,t+1}=1)=\{1+\exp[-1\cdot(\alpha+\lambda_1\cdot ROA_{i,t}+\lambda_2\cdot EQ_{i,t}^{M}\cdot ROA_{i,t}+\lambda_3\cdot EQ_{i,t}^{L}\cdot ROA_{i,t}$$
$$+\gamma_1\cdot EQ_{i,t}^{M}+\gamma_2\cdot EQ_{i,t}^{L}+\sum\beta\cdot other\ predictors_{i,t}+\varepsilon_{i,t})]\}^{-1}$$

where *Distress* indicator equals one when a firm experiences distress during the forecast horizon; EQ^M (EQ^L) is the indicator variable for medium (low) EQ; and *other variables* are all the predictive variables used in the Altman model other than *ROA*.

In the regression, λ_1 is the coefficient on *ROA* for the high EQ group. Because EQ^M (EQ^L) is a dummy variable, $\lambda_1+\lambda_2$ ($\lambda_1+\lambda_3$) represents the coefficients on *ROA* for the medium (low) EQ groups. Since high profitability should be associated with low distress risk, λ_1, $\lambda_1+\lambda_2$, and $\lambda_1+\lambda_3$ are all expected to be *negative*. Hypothesis H1a says that EQ should be positively associated with the informativeness of *ROA*. Because the magnitude, not the level, of the coefficient represents the informativeness of *ROA*, H1a implies that $|\lambda_1| > |\lambda_1+\lambda_2| > |\lambda_1+\lambda_3|$, which leads to the prediction that $\lambda_3 > \lambda_2 > 0$.

γ_1 (γ_2) measures the additional distress risk that firms bear when they move from high to medium (low) EQ group. If EQ reflects distress risk as hypothesis H2 suggests, we should observe *positive* γ_1 and γ_2, and, if the relation between EQ and distress risk is monotonic, we should also observe $\gamma_2 > \gamma_1 > 0$. Finally, if EQ helps predict financial distress, we should also

[16] Specifically, I interact earnings quality with *ROA* in the Altman model, *ROA* and *CHIN* in the Ohlson model, and *ROA* and π^{Merton} in the Bharath and Shumway model.

observe that the explanatory power, R^2, of the expanded models is higher than that of their original models.

3.4. Sample

My sample starts from the intersection of the Compustat annual file and CRSP monthly stock return file for NYSE, AMEX, and NASDAQ. It includes all the observations where the predictive variables and EQ measures are available. The sample period is 1985 to 2010 and is determined by the bankruptcy data available to me.

As shown in Table 1, my final sample includes 59,118 firm-year observations and 1,825 distress events, about 3% of the total sample. The time-series pattern of distress events appears consistent with macroeconomic conditions. The distress rate peaks at more than 5% around 2001 and 2002 when the internet bubble collapsed. Then it jumps again to more than 4% in 2008 during the recent financial crisis. Notice that my sample is smaller than others in the literature. This is because of the data restrictions imposed by the calculation of EQ measures.

<Insert table 1>

Table 2 presents the descriptive statistics of my sample. Panel A presents the summary statistics of the variables of interest in this study. These are the three EQ proxies, the distress predictors whose informativeness for distress is hypothesized to be influenced by EQ, and two variables capturing asset volatility: volatility of cash flows, denoted by *Vol*(*CF*), and volatility of returns, denoted by *Vol*(*Ret*). All the variables are winsorized at the 1 and 99 percentile. The distributions of these variables are in line with those of other studies (Bharath and Shumway 2008; Dichev and Tang 2009; Francis et al. 2005).

<Insert table 2>

Panel B presents the correlations among some of these variables. Consistent with previous studies, I find high correlation among the three EQ proxies. In particular, the correlations between *AQ* and *Vol*(*ΔE*) exceeds 0.5. The correlations between the EQ proxies and other variables are consistent with my hypotheses. For example, the high correlation between *Vol*(*Ret*) and EQ proxies is consistent with my hypothesis H1b. The high correlation between *Vol*(*CF*) and the EQ proxies is consistent with my hypothesis H2 as well as the findings in Dechow and Dichev (2002) and Francis et al. (2005).

4. Empirical Results

4.1. Main Analyses

Panel A, B, and C in Table 3 present the coefficient estimates for the Altman, the Ohlson, and the Bharath and Shumway models and their expanded models. Within each panel, Model 1 is the original model, and Models 2, 3, and 4 expand Model 1 based on three EQ measures, the absolute value of abnormal accruals, denoted by |*Acc*|, the accrual quality measure as in Francis et al. (2005), denoted by *AQ*, and the volatility of seasonally earnings, noted by *Vol*(*ΔE*). To save space, I only report coefficients on the variables relevant to my study.[17]

<Insert table 3>

Since firms with high profitability should be less likely to experience financial distress, the coefficients on *ROA* should be negative.[18] Because Hypothesis H1a implies that the

[17] Complete results are available upon request.

[18] The coefficient on *ROA* in Ohlson model is insignificant (see Model 1 of Panel B). The insignificance is driven by low earnings quality firms, and will be analyzed later this section.

magnitude of the coefficients on *ROA* should be smaller when the EQ is low than when it is high, H1a translates to positive coefficients on the interaction terms, $EQ^M \cdot ROA$ and $EQ^L \cdot ROA$, between *ROA* and indicators for medium (EQ^M) and low (EQ^L) EQ firms. This prediction is supported by Table 3. In Panel A, B, and C, the coefficients on $EQ^M \cdot ROA$ and $EQ^L \cdot ROA$ are mostly positive and significant. Furthermore, the magnitude of the coefficients on $EQ^M \cdot ROA$ and $EQ^L \cdot ROA$ suggests that EQ is monotonically associated with the informativeness of *ROA*; the informativeness of *ROA* is strongest when EQ is high, weakest when EQ is low, and is in between when EQ is medium.[19]

By taking into account the differences in EQ, we can recover information from *ROA* even when it is uninformative *on average*. In Panel B, the coefficient on *ROA* in the original Ohlson model is insignificant. But by separating firms into different EQ portfolios, expanded prediction models are able to utilize the information in *ROA* from firms with high and medium EQ.

Similarly, H1a implies that the magnitude of the coefficients on the change in net income (*CHIN*) should be smaller when EQ is low than when it is high in the Ohlson model. This translates to positive coefficients on $EQ^M \cdot CHIN$ and $EQ^L \cdot CHIN$ in Panel B of Table 3. However, this hypothesis is not supported. In an unreported further analysis, I revise the analysis of Panel B by interacting EQ with *CHIN*, but not with *ROA*. In this case, the coefficients on $EQ^L \cdot CHIN$ become significantly positive. This result suggests that even though EQ is associated with the informativeness of *CHIN*, this association is subsumed by the interaction between EQ and *ROA*. Therefore, in the subsequent analyses, I drop the interaction terms between EQ with *CHIN*.

[19] Untabulated results show that the difference between the coefficients on $EQ^M \cdot ROA$ and $EQ^L \cdot ROA$ is mostly statistically significant.

Table 3 provides support for hypothesis H1b as well. Because π^{Merton} is positively associated with distress risk, H1b implies *negative* coefficients on the interaction terms between implied risk and EQ indicators, $EQ^M \cdot \pi^{Merton}$ and $EQ^L \cdot \pi^{Merton}$. Results in Panel C support this hypothesis. The coefficients $EQ^L \cdot \pi^{Merton}$ are all negative and significant. Since π^{Merton} is a purely price-based predictive variable, this result suggests that EQ impacts the informativeness of both *accounting*- and *price*-based distress predictors.

Table 3 also provides support for hypothesis H2 that EQ is directly associated with distress risk. The coefficients on medium (EQ^M) and low (EQ^L) EQ indicators are generally positive and significant, suggesting that lower EQ is associated higher distress risk.[20] This result holds quite consistently across all the prediction models and EQ measures examined. To put things in perspective, in the Bharath and Shumway model, moving down from high EQ group to low EQ group is associated with an increase of the marginal probability of distress by 0.7% (0.6%) [1.2%] when EQ is measured by $|Acc|$ (AQ) [$Vol(\Delta E)$]; while an increase of one standard deviation of π^{Merton} is associated with an increase of marginal probability of distress by 1.3%.

Table 3 further shows that the expanded prediction models that take EQ into account perform better than their original models in terms of explanatory power, R^2.[21] Untabulated likelihood ratio tests show that the improvement is statistically significant across different models and earnings proxies. However, the economic magnitude of the improvement varies for different models. The improvement for the Altman models is most significant, with an increase in R^2 as high as 5 percentage points. But the improvement for the Ohlson and the Bharath and Shumway models is relatively modest, with an increase in R^2 less than 1.2 percentage points.

[20] This result holds if I sort firms into 2, 5, or 10 groups, or use continuous variables.

[21] The R^2 used in my analyses is McFadden's adjusted R^2. It mirrors the adjusted R^2 in OLS regressions by penalizing a model for including too many predictors.

One potential explanation is that different prediction models use predictive variables that correlate with EQ proxies to different degrees. My results are consistent with the Ohlson and the Bharath and Shumway models incorporating the impact of EQ more than the Altman model does.

To summarize, EQ influences the informativeness of predictive variables of distress and predicts distress by itself. The finding that EQ is *directly* associated with distress risk sheds new light on the documented association between EQ and debt contracting. For example, Bharath et al. (2008) find that firms with lower EQ are more likely to choose private, rather than public, debt, and the debt they borrow bears higher interest rates with shorter maturity. They interpret the results from an information perspective, arguing that the higher interest rate is a form of information risk premium. My study offers an alternative explanation. Since firms with lower EQ on average have higher distress risk, they might choose to use private debt to reduce the expected distress cost, such as restructuring costs, and then pay a higher interest rate to compensate creditors for bearing higher risk.

Hence, when examining whether information quality plays any role in the association between EQ and debt contracts, researchers should carefully control for the distress risk *directly* associated with EQ. However, this risk is not captured by the commonly-used controls for distress risk such as the Altman Z-score or the Ohlson O-score, because, as shown in my study, EQ measures are informative of financial distress even when added to these accounting-based prediction models. My study suggests a simple approach to solve this issue as follows. Researchers should first expand the prediction models such as those of Altman and Ohlson by adding the EQ measure of interest as a predictive variable to the models. The risk scores generated by these expanded models, therefore, capture the distress risk associated with the EQ measure, and can be used as appropriate control variables for distress risk.

4.2. Components of EQ Measures and the Prediction of Financial Distress

This subsection tries to disentangle two possible explanations for the documented direct association between EQ and distress risk. One possible explanation is that EQ is determined by firm fundamentals that might be associated with distress risk, such as firm size, cash flow volatility, and sales volatility (Dechow and Dicheve 2002). The other is that firms might manage earnings, thereby likely to have low EQ, prior to covenant violations when distress risk tends to be high (DeFond and Jiambalvo 1994; Sweeney 1994).

To disentangle these two possibilities, I follow the procedure introduced Francis et al. (2005) to decompose each of the EQ proxies – *AQ* and $Vol(\Delta E)$ – into two components, one capturing firm fundamentals (innate) and the other capturing managerial discretion (discretionary). I do not decompose |*Acc*| because, unlike the other two proxies, it is not a volatility measure. I run the following regression each year for each of the 48 Fama-French industries with at least 20 firms in the year.

$$\begin{aligned} EQ_{i,t} = {} & \lambda_0 + \lambda_1 \cdot size_{i,t} + \lambda_2 \cdot \sigma(CFO)_{i,t} + \lambda_3 \cdot \sigma(Sales)_{i,t} + \lambda_4 \cdot OperCycle_{i,t} \\ & + \lambda_5 \cdot NegEarn_{i,t} + \varepsilon_{i,t} \end{aligned}$$

where $EQ_{i,t}$ is the measures of EQ of firm *i* measured at *t*, $size_{i,t}$ is the log value of firm *i*'s total assets, $\sigma(CFO)_{i,t}$ is the standard deviation of firm *i*'s cash flows, as previously defined, over the past five years, $\sigma(Sales)_{i,t}$ is the standard deviation of firm *i*'s sales over the past five years,

$OperCycle_{i,t}$ is the log of the length of firm *i*'s operating cycle, and $NegEarn_{i,t}$ is the number of times firm *i* experienced losses in the past five years.

This procedure generates firm- and year- specific predicted values and residuals. The predicted value is the proxy for the innate component of EQ, *Innate EQ*, and the absolute value of the residuals is the proxy for the discretionary component, *Disc EQ*.[22] I treat these components as new EQ measures and use them to expand the prediction models, adding them as independent predictors and interacting them with *ROA* and π^{Merton} (depending on the model).

<Insert table 4>

Table 4 reports coefficient estimates of the prediction models and their expanded models. It provides an opportunity to examine how the innate and discretionary components of EQ influence the informativeness of *ROA* and π^{Merton}. In panel A and B, the coefficients on $EQ^M \cdot ROA$ and $EQ^L \cdot ROA$ are most positive and significant. In panel C, the results are weaker: only the coefficients on $EQ^M \cdot ROA$ and $EQ^L \cdot ROA$ in model 2 and 3 are significant. Moreover, in Model 2 and 4, the coefficients on $EQ^L \cdot \pi^{Merton}$ are significantly negative, consistent with what we observe in Table 3. This is not the case in Model 3 and 5, however: the coefficients on $EQ^M \cdot \pi^{Merton}$ and $EQ^L \cdot \pi^{Merton}$ are insignificant.

On balance, the results suggest that the association between EQ measures and the informativeness of distress predictors is driven by both the innate and discretionary components of EQ measures, but the innate component seems to play a bigger role. In a recent survey on the EQ literature, Dechow et al. (2010) observe that studies on managerial discretion are strongly

[22] The calculation of the innate and discretionary components of EQ further reduces my sample size by 20%.

represented in the literature, but the research on the impact of firm fundamentals on EQ is limited. They call for more research on the latter topic. Table 4 sheds light on this issue by providing analyses on how firm fundamentals and managerial discretion impact informativeness of distress predictors.

Turning attention to the association between components of EQ measures and distress risk, Table 4 shows that the coefficients on EQ^M and EQ^L are generally positive and significant, consistent with the results in Table 3. In an untabulated analysis, I put the innate component and discretionary components in the same regressions. In this case, the magnitude of the coefficients on the discretionary component is much smaller than the innate component, suggesting that firm fundamentals play a bigger role in explaining the association between EQ measures and distress risk. Overall, these results suggest the association between distress risk and EQ measures can be explained by the explanations based on firm fundamentals as well as based on managerial discretion.

4.3. Out-of-Sample Prediction

In Section 4.1, I show that incorporating the impact of EQ can improve the explanatory power of the prediction models. This raises the question whether the improvement of the in-sample analyses can be extended to out-of-sample tests. This subsection examines this issue. The analyses follow from the prior studies (Shumway 2001; Bharath and Shumway 2008) and are done in two steps. In the first step, I use the prediction models to calculate the out-of-sample distress risk scores for each firm each year. Specifically, to forecast the distress risk in year t+1, I first estimate model coefficients by using all the available observations from the beginning of my sample period to year *t*. With these coefficients and the predictive variables calculated with the data available at year t, I am able to generate the out-of-sample distress risk scores for each firm.

Based on these risk scores, firms are sorted into deciles each year. The top decile consists of risky firms that are most likely to experience distress over the next period, and the bottom five deciles consist of safest firms that should have the lowest probability of entering distress. I collapse the bottom five deciles into one big group, and call it safest group. I call the top decile riskiest group. For each group, I calculate the number of distressed firms captured by this group as a percentage of the total number of distressed firms in my sample. Because different models generate different risk scores, they also generate different groups. Intuitively, for a good model, the riskiest group should capture a high percentage of distressed firms, and the safest group should capture a low percentage of distressed firms. Based on this criterion, I compare the out-of-sample performance between the original models and their expanded models based on various EQ measures.

Table 5 compares the performance between original models and their expanded models. To facilitate comparison, the performance of the expanded models based on different EQ measures is presented as relative to that of their original models. Panel A (B) [C] shows the results based on the Altman (Ohlson) [Bharath and Shumway] type of models.

<Insert table 5>

Overall, the results in Table 5 correspond well to those on the explanatory power of the prediction models in Table 3. The expanded models based on |*Acc*| fail to show consistent improvement over their original models. The expanded models based on *AQ* show more consistent improvement over their original models, but only the improvement for the riskiest group in the Altman model reaches the level of significance. The expanded models based on *Vol*(Δ*E*) show the best improvement over their original models. The improvement for the Altman model is significant for both the riskiest and safest groups; and the improvement for the Ohlson model is significant for the safest group.

To summarize, the out-of-sample analyses generate mixed results. Expanded models based on EQ measures are not able to generate consistent improvement across different EQ measures and prediction models. Among different prediction models, the improvement of the expanded models is strongest for the Altman model, but much weaker for the Ohlson and Bharath and Shumway (2008) model. Among different EQ measures, *Vol*(Δ*E*) seems to be more effective in improving the performance of the prediction models.

The weaker results from out-of-sample analyses are perhaps not surprising. First, out-of-sample analyses use fewer observations and thus less information from the sample in forming the coefficient estimates. Second, distress is a rare event. Only 3% of my sample firms experience distress. Moreover, requirement to calculate EQ measures, especially *AQ*, further restricts my sample size. These factors make it difficult to detect the significant improvement for the expanded models. I will discuss more of the out-of-sample test in Section 5.2.2.

5. Robustness Tests

In Section 4, I provided supporting evidence for my hypotheses. This section tests the robustness of my results. To simplify the display of the results and increase the power of my test, the analyses in Section 5.2 and 5.3 are done by using only one EQ measure – *Vol*(*ΔE*).[23]

[23] The increased test power comes from a larger sample than the one previously used, because there is less data restriction when only the calculation of *Vol*(*ΔE*) is required. The results in Section 5.1 and 5.2 are similar if the

5.1. Sub-Period Analyses

To examine whether my results are driven by any specific sample period, I split my sample in two periods, 1985 – 1999 and 2000 – 2010. The results in Section 4.1 and 4.2 remain unchanged in these two sub-periods. EQ measures are significantly associated with the informativeness of *ROA* and π^{Merton}, and are directly associated with distress risk as well. These results hold for both components of EQ measures – that related to firm fundamentals and that related to managerial discretion.

5.2. Long Horizon Prediction

5.2.1. In-Sample Analyses

In this subsection, I examine whether the results in Section 4.1 are robust to the forecast horizon over which distress risk is estimated. The research design in this section is similar to that of Table 3 except that the forecast horizon varies from one year to three years.

Table 6 presents the coefficient estimates for prediction models across different forecasting horizons. The coefficient estimates for the one year horizon are mostly similar to what we have seen in Table 3. As the forecast horizon expands, the explanatory power of each model decreases noticeably. However, the associations between EQ measures and the informativeness of *ROA* and π^{Merton} remain rather stable, and the predictive power of EQ measures itself remains significant.[24] Moreover, the improvement in explanatory power of the expanded models over their original models remains little changed across different forecasting

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analyses are done based on other EQ measures, but the results in Section 5.3 become weaker, as is shown in Section 4.3. These results based on other EQ measures are available upon request.

[24] In the Ohlson model, however, the coefficient on ROA becomes positive, which is counter-intuitive. Untabulated analyses suggest that this is driven by firms with low earnings quality.

horizons.[25] Overall, Table 6 suggests that the results discussed in Table 3 are not sensitive to the forecasting horizon over which the distress risk is estimated.

<Insert table 6>

5.2.2. Out-of-Sample Analyses

This subsection compares the out-of-sample performance between the original prediction models and their expanded models with varying forecast horizons. Table 7 presents the results using the same methodology in Table 5. Each panel represents the comparisons within one type of model.

<Insert table 7>

The one-year prediction results in Table 7 are very similar to those shown in Table 5. The expanded model based on the Altman model significantly outperforms the original model, but the improvement for the Ohlson and the Bharath and Shumway models is weaker and does not pass any statistical test for the Ohlson model.[26]

As the forecasting horizon expands beyond one year, the prediction of all the models becomes much less precise. Riskiest groups capture fewer distressed firms, and safest groups capture more distressed firms. The improvement of the expanded models for the riskiest groups weakens. For the Altman model, the improvement for the riskiest group becomes insignificant when the forecasting horizon is three years. More encouraging, though, is the improvement for

[25] Take Panel A as an example. For one-year forecast, the R^2 of the expanded model is 5.1% higher than that in the original model, and the number is 5.1% and 4.5% for two- and three-year forecast respectively.

[26] Note that the sample in Table 6 is about 40% larger than the sample in Table 3, because I only require that data be available to calculate *Vol*(ΔE). The results would remain little changed if I use the sample in Table 3.

the safest groups: It remains relatively stable for the Altman model, and becomes much stronger for the Ohlson and the Bharath and Shumway models as the forecasting horizon expands.

The difference in improvement between the riskiest and the safest groups is potentially driven by their differences in firm compositions. The risky groups generated by the original models mostly consist of low EQ firms, with little variation in EQ, while the safest groups consist of firms with much higher variation in EQ.[27] Since there is more variation in EQ for the safest groups, the potential for improvement is higher.

Overall, even though the expanded models are not able to significantly improve the prediction for riskiest groups consistently, they do significantly improve the prediction for safest groups, especially when the forecast horizon is beyond one year. These results provide additional support for my hypotheses.

6. Conclusion

In this study, I investigate how EQ influences the predictive use of accounting information in debt markets, in the context of financial distress prediction. I hypothesize that EQ is positively associated with the informativeness of both accounting- and price-based distress predictors, and negatively associated with distress risk, itself. I test my hypotheses by applying them to three widely-used distress prediction models, those of Altman (1968), Ohlson (1980), and Bharath and Shumway (2008). I expand these models by using EQ measures as conditioning variables to interact with several earnings- and price-based predictors and as additional predictors per se. The estimated model coefficients provide consistent support for my

[27] Take the 3-year forecast of the Altman model for example. The top decile generated by the original model consists of 7.8%, 16.2%, and 76.0% of firms with high, medium, and low earnings quality respectively; while the same numbers for the bottom deciles are 40.5%, 37.5%, and 22.0%.

hypotheses. Further analyses suggest that the results are driven by components of EQ measures related to both firm fundamentals and managerial discretion. I also find that some, but not all, EQ measures improve the out-of-sample performance of the prediction models, especially when the forecast horizon is beyond one year.

My finding that EQ is *directly* associated with distress risk suggests that distress risk can potentially explain previously documented associations between EQ and different characteristics of debt contracts. Therefore, when determining whether information quality drives the association between EQ and debt contracts, researchers should control for the distress risk directly associated with EQ.

A. Appendix A – Variable Definition

Variable Names	Models	Variable Definition
RE/TA	Altman	Retained earnings / total assets = re / at
EBIT/TA	Altman	Earnings before interest & taxes / total assets = (pi + xint) / at
VE/TL	Altman	Market value of equity / total debt = (prcc_f*csho) / (dltt+dlc)
S/TA	Altman	Sales / total assets = sale / at
WC/TA	Altman, Ohlson	Working capital / total assets = (act - lct) / at
Size	Ohlson	Ln [total assets] = Ln (at / GNP index)
TL/TA	Ohlson	Total liabilities / total assets = (dltt + dlc) / at
CL/CA	Ohlson	Current liabilities / current assets = lct / act
FFO/TL	Ohlson	Free cash flow / total liabilities = (pi + dp) / (dltt + dlc)
INTWO	Ohlson	Indicator for cumulative loss in past two years = Indicator [ni + lag(ni) < 0]
OENEG	Ohlson	Indicator for negative stock holders' equity = Indicator (ceq < 0)
CHIN	Ohlson	Change in net income = [ni - lag(ni)] / [|ni| + |lag(ni)|]
NI/TA	Ohlson, BS	Net income / total assets = ni / at
Debt	BS	Ln(debt) = Ln(dltt + dlc)
Equity	BS	Ln(market value of equity) = Ln(prcc_f*csho)
1/Vol(Ret)	BS	1 / Annualized monthly return volatility = 1 / [Std(Ret)*(12^0.5)]
Ex Ret	BS	Excess return over the past 12 month = $\text{Return}_{i,\,t-1} - \text{Market Return}_{i,\,t-1}$
π^{Merton}	BS	Implied distress risk $= \frac{\ln[(Debt + MV(Equity)) / MV(Equity)] + (ret_{it-1} - 0.5 \cdot \sigma_v^2) \cdot T}{\sigma_v \cdot \sqrt{T}}$ where $\sigma_v = \frac{E}{E+D} \cdot \sigma_{ret} + \frac{D}{E+D} \cdot (0.05 + 0.25 \cdot \sigma_{ret})$

B. Appendix B – Tables (Main Tests)

Table 1

The Number of Firms and Distress Events by Year

This table presents the number of firms and distress events by year for my sample. The sample consists of NYSE, AMEX, and NASDAQ firms for which all distress predictors and EQ measures used in my study are available. (See the Appendix and the research design section for a listing of all the variables.) Active firms are those that have not experienced distress at the beginning of the calendar year. Financial distress is defined as a bankruptcy, default, or performance-related delisting. Firms are eliminated from the sample after their first incidence of distress.

Calendar Year	Active Firms	Number of Distress	Percent of Distressed firms
1985	2357	40	1.70%
1986	2237	58	2.59%
1987	2135	38	1.78%
1988	2123	44	2.07%
1989	2034	38	1.87%
1990	2096	61	2.91%
1991	2133	82	3.84%
1992	2176	88	4.04%
1993	2298	60	2.61%
1994	2411	57	2.36%
1995	2464	43	1.75%
1996	2461	36	1.46%
1997	2447	66	2.70%
1998	2428	102	4.20%
1999	2357	106	4.50%
2000	2371	96	4.05%
2001	2317	119	5.14%
2002	2273	116	5.10%
2003	2429	103	4.24%
2004	2387	59	2.47%
2005	2315	71	3.07%
2006	2370	47	1.98%
2007	2309	72	3.12%
2008	2189	74	3.38%
2009	2126	102	4.80%
2010	1875	47	2.51%
Total	59118	1825	3.09%

Table 2

Descriptive Statistics

This table presents descriptive statistics for the variables employed in this study. The sample contains 59,118 firm-year observations over the sample period of 1985 to 2010, with 1,825 distress events. In Panel A are the distributions of the variables. In Panel B is the correlation matrix for the variables, with Pearson correlations below the diagonal and Spearman correlations above the diagonal. |Acc| is absolute value of abnormal accruals; AQ is accrual quality as in Francis et al. (2005); Vol(ΔE) is the standard deviation of seasonally adjusted quarterly earnings over the past 12 quarters; EBIT/TA is earnings before interest and tax over total assets; NI/TA is net income over total assets; πMerton is implied distress risk, as in Bharath and Shumway (2008); Vol(CF) is the standard deviation of operating cash flows over the past five years; Vol(Ret) is the annualized volatility of the monthly returns over the past 12 months. All variables except πMerton are winsorized at the 1 and 99 percentage level. All the correlations are significant at 1% level.

Panel A: Summary Information of Variables of Interest

	Mean	10%	25%	Median	75%	90%
$\lvert Acc \rvert$	0.070	0.007	0.019	0.044	0.089	0.159
AQ	0.052	0.013	0.023	0.039	0.067	0.107
$Vol\ (\Delta E)$	0.038	0.003	0.007	0.015	0.039	0.089
$EBIT/TA$	0.027	-0.142	0.011	0.077	0.124	0.178
NI/TA	-0.022	-0.176	-0.019	0.034	0.070	0.110
$CHIN$	0.005	-1.000	-0.286	0.046	0.284	0.997
π^{Merton}	0.078	0.000	0.000	0.000	0.009	0.283
$Vol(CF)$	0.082	0.020	0.034	0.060	0.103	0.165
$Vol(Ret)$	0.474	0.191	0.268	0.394	0.587	0.848

Panel B: Correlation Matrix

	$\lvert Acc \rvert$	AQ	$Vol\ (\Delta E)$	$EBIT/TA$	NI/TA	$\lvert CHIN \rvert$	π^{Merton}	$Vol(CFO)$	$Vol(Ret)$
$\lvert Acc \rvert$		0.42	0.28	-0.12	-0.09	0.17	0.12	0.39	0.26
AQ	0.45		0.57	-0.25	-0.20	0.28	0.24	0.70	0.47
$Vol\ (\Delta E)$	0.25	0.51		-0.42	-0.37	0.52	0.33	0.60	0.52
$EBIT/TA$	-0.22	-0.35	-0.51		0.91	-0.43	-0.47	-0.25	-0.31
NI/TA	-0.21	-0.33	-0.51	0.93		-0.42	-0.52	-0.22	-0.29
$\lvert CHIN \rvert$	0.12	0.18	0.20	-0.13	-0.09		0.33	0.33	0.35
π^{Merton}	0.08	0.11	0.14	-0.24	-0.25	0.18		0.27	0.64
$Vol(CF)$	0.38	0.65	0.62	-0.42	-0.42	0.23	0.14		0.48
$Vol(Ret)$	0.23	0.40	0.37	-0.37	-0.36	0.24	0.37	0.41	

Table 3

Estimates of Distress Prediction Models Expanded by EQ Measures

This table reports coefficient estimates of the distress prediction models and their expanded models that add EQ measures as conditioning variables for ROA, CHIN, and πMerton and as additional predictors. In Panel A (B) [C] are the coefficient estimates of the Altman (Ohlson) [Bharath and Shumway] model and its expanded models. The dependent variable is the distress indicator. EQM (EQL) is the indicator variable for medium (low) EQ firms; ROA is EBIT (net income) over total assets in the Altman (Ohlson, and Bharath and Shumway) model; CHIN is the change in earnings deflated by the sum of the asolute value of the earnings of the past two years; πMerton is the implied disress risk, as in Bharath and Shumway (2008). EQ measures are |Acc|, absolute value of abnormal accruals; AQ, accrual quality as in Francis et al. (2005); Vol(ΔE), the volatility of seasonally adjusted quarterly earnings. Estimated coefficients on other predictors (see the Appendix for variable definitions) are not reported. All variables are measured at three months after the firms' fiscal year end. The sample contains 59,118 firm-year observations from 1985 to 2010, with 1,825 distress events. The R2 is adjusted to mirror the adjusted R2 in OLS regressions. Absolute value of z-statistics, based on Huber-White standard errors, is reported in parentheses below the estiamted coefficient value. *** (**) [*] represents significant at 1% (5%) [10%].

Panel A: The Altman Model

	Pred. Sign	Original Model	Expanded Models Based on EQ Measures		
			|Acc|	*AQ*	*Vol (ΔE)*
		(1)	(2)	(3)	(4)
ROA	-	-1.82***	-2.38***	-2.93***	-11.86***
		(14.79)	(7.41)	(8.62)	(6.04)
$EQ^M \cdot ROA$	+		0.25	0.81**	6.75***
			(0.67)	(2.07)	(3.36)
$EQ^L \cdot ROA$	+		1.02***	1.64***	10.72***
			(3.20)	(4.69)	(5.46)
EQ^M	+		0.27***	0.54***	0.46**
			(3.52)	(6.22)	(2.52)
EQ^L	+		0.86***	1.28***	1.23***
			(12.27)	(16.21)	(6.80)
R^2		17.6%	18.8%	20.0%	22.4%

Panel B: The Ohlson Model

	Pred. Sign	Original Model	Expanded Models Based on EQ Measures		
			|Acc|	*AQ*	*Vol (ΔE)*
		(1)	(2)	(3)	(4)
ROA	-	0.02	-0.51***	-0.89***	-7.18***
		(0.26)	(3.42)	(3.66)	(5.37)
$EQ^M \cdot ROA$	+		0.36*	0.66**	5.42***
			(1.86)	(2.40)	(3.95)
$EQ^L \cdot ROA$	+		0.69***	1.02***	7.22***
			(4.24)	(4.09)	(5.40)
CHIN	-	-0.63***	-0.78***	-0.59***	-0.50**
		(13.05)	(7.38)	(4.55)	(2.02)
$EQ^M \cdot CHIN$	+		0.10	0.09	-0.04
			(0.70)	(0.55)	(0.16)
$EQ^L \cdot CHIN$	+		0.28**	-0.06	0.01
			(2.29)	(0.40)	(0.04)
EQ^M	+		0.17**	0.29***	0.60***
			(2.02)	(3.29)	(5.35)
EQ^L	+		0.53***	0.60***	1.07***
			(6.49)	(7.00)	(9.56)
R^2		21.7%	22.1%	22.1%	22.9%

Panel C: The Bharath and Shumway Model

	Pred. Sign	Original Model	Expanded Models Based on EQ Measures		
			$\lvert Acc \rvert$	AQ	$Vol\ (\Delta E)$
		(1)	(2)	(3)	(4)
ROA	-	-1.27***	-1.62***	-1.37***	-5.74***
		(16.88)	(8.77)	(4.71)	(4.08)
$EQ^M \cdot ROA$	+		0.29	0.16	2.82*
			(1.18)	(0.48)	(1.94)
$EQ^L \cdot ROA$	+		0.49**	0.14	4.64***
			(2.52)	(0.48)	(3.29)
π^{Merton}	+	1.16***	1.63***	1.60***	1.55***
		(8.46)	(8.59)	(7.49)	(4.96)
$EQ^M \cdot \pi^{Merton}$	-		-0.22	-0.24	-0.04
			(1.05)	(1.07)	(0.11)
$EQ^L \cdot \pi^{Merton}$	-		-0.85***	-0.68***	-0.67**
			(4.60)	(3.32)	(2.17)
EQ^M	+		0.18	0.15	0.36**
			(1.64)	(1.26)	(2.29)
EQ^L	+		0.71***	0.61***	1.13***
			(7.23)	(5.56)	(7.68)
R^2		27.4%	27.8%	27.7%	28.4%

Table 4

Estimates of Distress Prediction Models Expanded by Different Components of EQ Measures

This table reports coefficient estimates of the distress prediction models and their expanded models that use components of EQ measures as conditioning variables for ROA and πMerton and as additional predictors. To run the analyses, each EQ measure, namely AQ and Vol(ΔE), is first decomposed into two components (Francis et al. 2005) – that related to firm fundamentals (Innate EQ), and that related to managerial discretion (Disc EQ). Each components then is treated as a new EQ measure to expand the prediction models. In Panel A (B) [C] are the coefficient estimates of the Altman (Ohlson) [Bharath and Shumway] model and its expanded models. The dependent variable is the distress indicator. EQM (EQL) is the indicator variable for medium (low) EQ firms; ROA is EBIT (net income) over total assets in the Altman (Ohlson, and Bharath and Shumway) model; πMerton is the implied disress risk, as in Bharatha and Shumway (2008). Estimated coefficients on other predictors (see the Appendix for variable definitions) are not reported. All predictors are measured at three months after the firms' fiscal year end. The sample contains 49,876 firm-year observations from 1985 to 2010, with 1,394 distress events. The R2 is adjusted to mirror the adjusted R2 in OLS regressions. Absolute value of z-statistics, based on Huber-White standard errors, is reported in parentheses below the estiamted coefficient value. *** (**) [*] represents significant at 1% (5%) [10%].

Panel A: The Altman Model

	Pred. Sign	Original Model	Expanded Models Based on EQ Measures			
			Innate AQ	*Disc AQ*	*Innate Vol(ΔE)*	*Disc Vol(ΔE)*
		(1)	(2)	(3)	(4)	(5)
ROA	-	-2.31***	-4.96***	-3.23***	-8.48***	-4.22***
		(13.31)	(7.91)	(7.75)	(6.80)	(7.73)
$EQ^M \cdot ROA$	+		0.77***	0.33***	0.52***	0.24***
			(6.51)	(3.73)	(3.39)	(2.70)
$EQ^L \cdot ROA$	+		1.61***	0.88***	1.40***	0.81***
			(14.52)	(10.65)	(9.71)	(9.75)
EQ^M	+		1.93***	0.40	2.51*	1.60***
			(2.68)	(0.92)	(1.93)	(2.73)
EQ^L	+		3.44***	1.58***	7.04***	2.45***
			(5.36)	(3.91)	(5.62)	(4.58)
R^2		18.8%	22.4%	20.1%	23.3%	20.2%

Panel B: The Ohlson Model

	Pred. Sign	Original Model	Expanded Models Based on EQ Measures			
			Innate AQ	*Disc AQ*	*Innate Vol(ΔE)*	*Disc Vol(ΔE)*
		(1)	(2)	(3)	(4)	(5)
ROA	-	0.06	-3.39***	-0.70**	-2.94***	-0.87**
		(0.45)	(5.88)	(3.04)	(3.68)	(3.00)
$EQ^M \cdot ROA$	+		2.63***	0.28	0.11	0.93***
			(4.27)	(1.05)	(0.12)	(2.77)
$EQ^L \cdot ROA$	+		3.56***	0.98***	3.03***	1.01***
			(6.19)	(4.25)	(3.81)	(3.53)
EQ^M	+		0.53***	0.20**	0.55***	0.21**
			(4.62)	(2.17)	(4.41)	(2.28)
EQ^L	+		0.93***	0.44***	1.13***	0.42***
			(8.04)	(4.97)	(9.19)	(4.70)
R^2		22.1%	22.9%	22.4%	23.2%	22.3%

Panel C: The Bharath and Shumway Model

	Pred. Sign	Original Model	Expanded Models Based on EQ Measures			
			Innate AQ	*Disc AQ*	*Innate Vol* (ΔE)	*Disc Vol* (ΔE)
		(1)	(2)	(3)	(4)	(5)
ROA	-	-1.50***	-2.38***	-1.91***	-1.39	-2.02***
		(14.02)	(4.41)	(6.63)	(1.13)	(4.41)
$EQ^M \cdot ROA$	+		0.88	0.06	-1.84	0.40
			(1.38)	(0.17)	(1.41)	(0.73)
$EQ^L \cdot ROA$	+		0.96*	0.58*	0.06	0.64
			(1.75)	(1.95)	(0.05)	(1.38)
π^{Merton}	+	1.17***	1.71***	1.32***	1.90***	1.39***
		(7.42)	(6.34)	(5.69)	(5.50)	(6.02)
$EQ^M \cdot \pi^{Merton}$	-		-0.25	-0.07	-0.47	-0.12
			(0.84)	(0.27)	(1.27)	(0.46)
$EQ^L \cdot \pi^{Merton}$	-		-0.76***	-0.27	-0.93***	-0.38
			(2.92)	(1.21)	(2.76)	(1.63)
EQ^M	+		0.15	0.09	0.30*	0.10
			(0.99)	(0.72)	(1.79)	(0.82)
EQ^L	+		0.74***	0.40***	1.05***	0.47***
			(5.00)	(3.58)	(6.70)	(4.26)
R^2		27.7%	28.1%	27.9%	28.4%	27.9%

Table 5

Comparisons of the Out-of-Sample Predictions between the Prediction Models and Their Expanded Models Based on EQ Measures

This table compares the out-of-sample prediction between the prediction models and their expanded models based on measures of EQ. To make the comparison, I first use the prediction models to generate out-of-sample distress risk estimates for each firm each year, using all the available information up to the forecast date, and then rank firms into deciles with these estimates each year. Top decile contains the riskiest firms, and is named as the riskiest group in the table. The bottom five deciles contain the safest firms and are collapsed into one big group which is named as the safest group in the table. For each group, I calculate the number of distressed firms captured by that group as a percentage of the total number of distressed firms in my sample. The percentages for the expanded models are presented as relative to those of their original models. The sample contains 54,851 firm-year observations from 1987-2010, with 1,717 distressed events. *** (**) [*] represents significant at 1% (5%) [10%] (one-sided chi-square test).

Panel A: The Altman Model

Deciles	Original Model	Pred. Sign	Expanded Models Based on EQ Measures		
			$\lvert Acc \rvert$	AQ	$Vol\ (\Delta E)$
Safest	11.0%	-	-0.8%	-1.9% ***	-3.4% ***
Riskiest	58.1%	+	-0.9%	0.8%	2.4% *

Panel B: The Ohlson Model

Deciles	Original Model	Pred. Sign	Expanded Models Based on EQ Measures		
			$\lvert Acc \rvert$	AQ	$Vol\ (\Delta E)$
Safest	8.0%	-	0.1%	-0.1%	-1.0% *
Riskiest	57.0%	+	0.2%	0.6%	0.8%

Panel C: The Bharath and Shumway Model

Deciles	Original Model	Pred. Sign	Expanded Models Based on EQ Measures		
			$\lvert Acc \rvert$	AQ	$Vol\ (\Delta E)$
Safest	4.8%	-	-0.3%	0.1%	0.2%
Riskiest	63.5%	+	0.3%	0.9%	1.5%

Table 6

Long-Horizon Analyses: Estimates of Distress Prediction Models

This table reports coefficient estimates of the distress prediction models and their expanded models that use Vol(ΔE) as conditioning variables for ROA and πMerton and as additional predictors. The forecast horizon over which distress risk is estimated varies from one year to three years. In Panel A (B) [C] are coefficient estimates of the Altman (Ohlson) [Barath and Shumway] model and its expanded models. The dependent variable is the distress indicator. Vol(ΔE)M [Vol(ΔE)H] is the indicator variable for firms with medium [high] volatility of seasonally adjusted earnings, and high Vol(ΔE) indicates low EQ. ROA is EBIT (net income) over total assets in the Altman (Ohlson, and Barath and Shumway) model; πMerton is the implied disress risk, as in Barath and Shumway (2008). Estimated coefficients on other predictors (see the Appendix for variable definitions) are not reported. All predictors are measured at three months after the firms' fiscal year end. One-year sample contains 83,785 firm-year observations and 3,420 distress events; two-year sample contains 80,989 firm-year observations and 3,245 distress events; three-year sample contains 77,913 firm-year observations and 2,797 distress events. The sample used here is larger than the one used in Table 3 because it does not require the calculation of AQ. The R2 is adjusted to mirror the adjusted R2 in OLS regressions. Absolute value of z-statistics, based on Huber-White standard errors, is reported in parentheses below the estiamted coefficient value. *** (**) [*] represents significant at 1% (5%) [10%].

Panel A: The Altman Model

	Pred.	One Year		Two Years		Three Years	
	Sign	Original	Expanded	Original	Expanded	Original	Expanded
ROA	-	-1.45***	-10.70***	-1.13***	-11.23***	-0.99***	-10.35***
		(22.17)	(10.97)	(17.64)	(13.03)	(15.51)	(12.74)
$Vol(\Delta E)^M \cdot ROA$	+		6.73***		7.88***		6.90***
			(6.59)		(8.78)		(8.21)
$Vol(\Delta E)^H \cdot ROA$	+		9.79***		10.65***		9.89***
			(10.03)		(12.36)		(12.16)
$Vol(\Delta E)^M$	+		0.39***		0.16*		0.21**
			(3.95)		(1.72)		(2.29)
$Vol(\Delta E)^H$	+		1.30***		0.90***		0.77***
			(13.44)		(10.29)		(8.70)
R^2		16.2%	21.3%	6.1%	11.2%	3.7%	8.2%

Panel B: The Ohlson Model

	Pred.	One Year		Two Years		Three Years	
	Sign	Original	Expanded	Original	Expanded	Original	Expanded
ROA	-	-0.08*	-5.80***	0.12**	-6.49***	0.23***	-6.14***
		(1.73)	(7.98)	(2.17)	(9.50)	(3.45)	(8.49)
$Vol(\Delta E)^M \cdot ROA$	+		4.24***		5.25***		4.86***
			(5.71)		(7.50)		(6.55)
$Vol(\Delta E)^H \cdot ROA$	+		5.75***		6.65***		6.40***
			(7.93)		(9.78)		(8.89)
$Vol(\Delta E)^M$	+		0.52***		0.41***		0.42***
			(6.59)		(6.14)		(6.03)
$Vol(\Delta E)^H$	+		1.07***		0.92***		0.77***
			(13.73)		(13.47)		(10.76)
R^2		21.0%	22.1%	12.3%	13.6%	9.3%	10.5%

Panel C: The Bharath and Shumway Model

	Pred.	One Year		Two Years		Three Years	
	Sign	Original	Expanded	Original	Expanded	Original	Expanded
ROA	-	-0.99***	-5.04***	-0.65***	-5.81***	-0.56***	-4.81***
		(22.99)	(5.59)	(15.97)	(7.62)	(12.54)	(6.35)
$Vol(\Delta E)^M \cdot ROA$	+		2.69***		3.98***		2.78***
			(2.85)		(4.91)		(3.47)
$Vol(\Delta E)^H \cdot ROA$	+		4.21***		5.32***		4.40***
			(4.66)		(6.97)		(5.79)
π^{Merton}	+	1.15***	1.42***	0.72***	1.01***	0.51***	1.11***
		(11.27)	(6.77)	(8.03)	(6.00)	(6.04)	(7.06)
$Vol(\Delta E)^M \cdot \pi^{Merton}$	-		0.08		-0.02		-0.46***
			(0.34)		(0.11)		(2.64)
$Vol(\Delta E)^H \cdot \pi^{Merton}$	-		-0.60***		-0.66***		-1.00***
			(2.89)		(3.94)		(6.11)
$Vol(\Delta E)^M$	+		0.27**		0.27***		0.48***
			(2.41)		(2.76)		(5.00)
$Vol(\Delta E)^H$	+		1.19***		1.09***		1.11***
			(11.40)		(11.72)		(11.75)
R^2		26.6%	27.9%	14.2%	15.6%	9.9%	11.3%

Table 7

Long-Horizon Analyses: Out-of-Sample Prediction

This table compares the out-of-sample prediction between the prediction models and their expanded models based on Vol(ΔE). The forecast horizon varies one year to three years. To make the comparison, I first use the prediction models to generate out-of-sample distress risk estimates for each firm each year, using all the available information up to the forecast date, and then rank firms into deciles with these estimates each year. Top decile contains the riskiest firms, and is named as the riskiest group in the table. The bottom five deciles contain the safest firms, and are collapsed into one big group which is named as the safest group in the table. For each group, I calculate the number of distressed firms captured by that group as a percentage of the total number of distressed firms in my sample. The percentages for the expanded models are presented as relative to those of their original models. The one-year sample contains 75,187 firm-year observations and 3,130 distress event; the two-year sample contains 72,051 firm-year observations and 2,976 distress events; and the three-year sample contains 69,132 firm-year observations and 2,556 distress events. The sample used here is larger than the one used in Table 5 because it does not require the calculation of AQ. *** (**) [*] represents significant at 1% (5%) [10%] (one-sided chi-square test).

Panel A: The Altman Model

	One-Year		Two-Year		Three-Year	
	Original	Expanded	Original	Expanded	Original	Expanded
Safest	11.3%	-3.8% ***	17.8%	-5.5% ***	20.5%	-4.1% ***
Riskiest	54.0%	1.7% *	36.2%	1.3% *	30.4%	0.5%

Panel B: The Ohlson Model

	One-Year		Two-Year		Three-Year	
	Original	Expanded	Original	Expanded	Original	Expanded
Safest	7.5%	-0.5%	13.8%	-2.3% ***	16.3%	-2.2% ***
Riskiest	53.2%	0.6%	37.7%	0.0%	33.1%	0.7%

Panel C: The Bharath and Shumway Model

	One-Year		Two-Year		Three-Year	
	Original	Expanded	Original	Expanded	Original	Expanded
Safest	5.5%	-0.8% **	11.5%	-2.3% ***	15.9%	-2.7% ***
Riskiest	59.1%	0.9%	41.1%	1.1%	33.9%	0.7%

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