Two Paths to Financial Distress

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Abstract

One of the findings that emerges from recent empirical studies is that financially distressed stocks have large dispersion in their BM. In this paper we suggest a rational explanation for this phenomenon. Our main argument is that the likelihood of a firm becoming either low or high BM as it becomes distressed largely depends on the correlation between the cash flows of current and future projects. We develop a simple model that accounts for this correlation. Our model's predictions are largely consistent with prior evidence documented in the literature. Furthermore, our model also yields new predictions that are supported by our empirical tests.

1. Introduction

Financial distress plays a major role in assessing the risk of the firm (Chan and Chen 1991). Fama and French (1992, 1993) argue that both size and the book to market equity ratio (BM) are proxies for the distress risk factor. According to the Fama and French argument high BM stocks are more exposed to the distress risk factor and hence represent greater risk for investors. Numerous papers examine the relation between the financial health of the firm and its BM. One commonly used approach is to examine the financial health of the firm using bankruptcy models. These studies reveal several unexpected results that are not in line with the Fama and French argument. One of these findings is the fact that stocks in financial distress have large dispersion in their BM (e.g. Dichev 1998 and Campbell et al 2007). Furthermore, the composition of the distressed portfolio seems to be dependent on the type of model used to assess the financial health of the firm. Papers that use accounting based model such as the Altman Z-score and the Ohlson O-score report that most of the stocks in the distressed portfolio are low BM stocks (e.g. Dichev 1998 and Griffin and Lemmon 2002). Conversely, papers that use market based models report that most of the stocks in the distressed portfolio are high BM (Vassalou and Xing 2004).

To date, the academic literature has struggled to explain the above findings.[1] Campbell et al (2007) argue that the high dispersion in BM is due to the fact that

[1] Most of the recent financial distress literature focuses on the ex-post returns of financially distressed stocks. The empirical finding that emerges is that financially distressed stocks earn lower returns than healthy stocks. Papers that investigate the returns of financially distressed stocks include Dichev 1998, Griffin and Lemmon 2002, Fang and Zhong, 2004, Vassalou and Xing 2004, Agrawal and Thafler 2005, Avramov et al 2006, Chen and Chollete 2006, Garlappi et al 2006, Bali et al 2006, Campbell et al 2007, George and Hwang 2007.

financially distressed firms differ in the rate at which they lose their market and book value.[2] Yet, the reasoning behind this argument is left unexplained. In this paper we seek to fill this void. We argue that the high dispersion in BM value is due to the fact that stocks are likely to follow two distinct paths as they become financially distressed. We start by considering a firm that receives a negative shock to its earnings that drives it into financial distress. Previous studies typically suggest that these stocks will suffer losses in both market and book value. However, since book values are assumed to lag behind market values the end result will be an *increase* in BM. Conversely, we argue that the effect of a negative shock on the firm's BM is not straightforward and largely depends on the correlation between the cash flows of current and future projects (henceforth *correl*). Factors that are likely to affect *correl* include the similarity in products between current and future projects, the similarity in technologies used and the similarity in pricing and strategy in the markets where the firm operates.

Whether BM increases or decreases following a negative shock depends on the initial value of BM as well as *correl*. A firm with a higher *correl* will have a greater decrease in market value following a negative shock than an otherwise similar firm with a lower *correl*. Thus a negative shock is more likely to give rise to an increase in BM for firms with higher *correl.* That BM possibly decreases following a negative shock can be shown with the following simple example. Consider the case of firms for which the cash flows from current and future projects are uncorrelated. A negative shock to the current project of such a firm will have no impact on the value of the future project. Hence, in this extreme case, the loss in market value will not exceed that in book value.

[2] Garlappi and Yan (2007) offer another reason for divergence in characteristics for firms in financial distress, arguing that differences in their financial leverage may lead to difference in returns patterns.

Consequently, firms that initially have BM lower than *one* will suffer a decrease in BM following a negative shock.

In the more realistic case of firms where current and future projects are correlated, the cash flows of future projects are likely to decrease following a negative shock to the current project. In this situation the effect of a negative shock can be analyzed using Merton's (1974) model of risky debt, where equity is modeled as a call option on the assets of the firm with strike price equal to the face value of debt. Financially distressed firms are those where the call option is close-to-the-money. Therefore, financially distressed firms have a lower delta than financially healthy firms and will suffer a smaller decrease in market value as a result of a negative shock. Furthermore, a shock to earnings is likely to result in an increase in volatility of assets and a subsequent increase in market value.[3], [4] Because vega is greatest for at-the-money options, financially distressed firms have the greatest sensitivity to any increase in volatility. The joint impact of delta and vega implies that financially distressed firms are most likely to suffer the smallest decrease in market value (or even an increase) following a negative shock. Consequently a decrease in BM following negative news should be mainly observed among financially distressed stocks. Our empirical findings are consistent with this argument.

We develop a simple two-period model that has empirically testable time series and cross-sectional predictions. In the model the firm faces two projects – current and

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[3] Various papers confirm that volatility increases following both positive and negative news (e.g. Black 1976, Christie 1982, Glosten et al 1993 etc'). However, the increase in volatility is larger after a negative shock. Black (1976), Christie (1982) and Schwert (1989) among others demonstrated that the asymmetric increase in volatility cannot be explained by leverage effect, suggesting that negative shock lead to increase in asset volatility. Campbell et al (2007) report very high volatility for financially distressed stocks, Fang and Zhong (2004) report an increase in assets volatility for financially distressed firms.

[4] In our model framework *correl* is unobservable. Thus investors must estimate its value. Errors in the estimation will lead to an increase in the uncertainty regarding future cash flows of the firm. This effect will be more pronounced for firms that receive a shock to current earnings. Note that for firms that report expected earnings errors in estimation of *correl* will not affect the market value of the firm.

future. At some point the firm receives a negative shock to its current project. This negative shock causes the value of the firm's assets to decrease and approach the value of debt. We examine the effect of this negative shock on BM and other characteristics of the firm. Consistent with the above intuition, our model results show that a negative shock to the firm can lead to two types of financial distress. The first type of financially distressed firm is the 'classic' distressed firm. These firms have typically high *correl* and tend to have low growth opportunities. They are characterized by a high book to market equity ratio, high debt to equity ratio and low survival rates after a negative shock to current projects. The second type of firm in financial distress tends to have low *correl* and relatively large growth opportunities. These stocks are characterized by a low BM ratio, relatively low debt to equity ratio, higher uncertainty regarding future market values and higher probability of surviving after a failure of current projects. Our empirical findings are consistent with our model predictions.

A long line of literature studies the persistence and predictability of earnings (e.g. Beaver 1970, Brooks and Buckmaster 1976, Fama and French 2000).[5] In a related finding, Basu (1997) reports that earnings persistence is lower for stocks with negative earnings changes. Various papers examine earnings persistence using value multiples. However, to the best of our knowledge, there has been no direct testing of the relation that links *persistence coefficients* to book-to-market value. Griffin and Lemmon (2002) argue that investors systematically underestimate the correlation between past and future projects, resulting in low BM values and ex-post underperformance. Our paper differs from Griffin and Lemmon in two important aspects. First, our model is completely

[5] It has been found that earnings and profitability are mean reverting and predictable. More importantly, the observed persistence is heterogeneous (Fama and French 2000, Chan, Karceski, Lakonishok 2003).

rational and shows that a decrease in BM is expected for low correlation stocks regardless of the mispricing reported in Griffin and Lemmon. Indeed, in the empirical section, we account for the possible mispricing and show that the results are robust to such amendment. Second, our focus is the importance of the distinction between the two types of financial distress, whereas Griffin and Lemmon focus on the ex-post performance of these stocks.

The importance of the distinction between low BM financially distressed (LFD) firms and high BM financially distressed (HFD) firms is threefold. First, the division into two types of financial distress sheds insight into many results that are reported in the literature. Among results that our model helps to explain are the large dispersion in BM (Dichev 1998), the differences in results produced by accounting and market based models (Griffin and Lemmon (2002) and Vassalou and Xing (2004)) and the better predictive ability of net income to market value of assets compared to net income to total assets (Campbell et al. 2007). Second, the fact that BM can decrease as a result of financial distress casts doubt on the use of variables such as Tobin's Q to measure the performance of these firms. Finally, the distinction between the two types of financially distressed stocks is helpful in understanding the relative strengths and weaknesses of models and variables that are used to predict financial distress. Our empirical findings suggest that the predictive ability of a model is largely driven by its ability to select the right proportion of the two different types of financial distress into the distressed portfolio.

The rest of the paper is organized as follows: In section II we develop the model, Section III contains the data, methodology and descriptive statistics, Section IV presents the empirical findings and section V discuss the implication of our findings and Section VI concludes.

2. Model

In this section we develop a simple model to illustrate the effects of the correlation between the cash flows of current and future projects. After the setup, we first show that the correlation is closely related to continuation of the firm (the survivability) under very general conditions. Then we show that with all equity financing, the change in BM after a negative shock depends on *correl*. Last we consider the case with debt financing. We show the above results still hold, and most importantly, the effect is strongest for financially distressed firms.

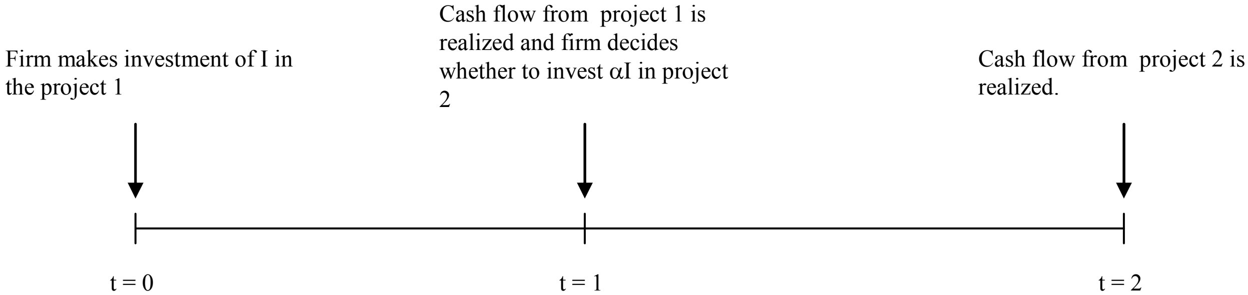
2.1 Set Up

There are two periods and three dates, t = 0, 1, 2. The cash flows of the projects are independently distributed across firms at all times. All firms commence a project at t = 0, which requires investment I. The cash flow of the project is given by $\tilde{F}_1 = \mu_1 + \varepsilon_1$. The cash flows from the available project at t = 1 depends on the realization F_1. We assume an AR(1) process for earnings. Additionally, we account for the possibility of scaling the future project by introducing scaling parameter α. Thus, the future project require an investment of αI at t = 1, and generates a payoff of α at time t = 2. The distribution of $\tilde{F}_2$ is:

$$\tilde{F}_2 - \mu_2 = \rho(\tilde{F}_1 - \mu_1) + \varepsilon_2 \text{ and } \tilde{F}_1 = \mu_1 + \varepsilon_1 \qquad (2.1)$$

where $\rho \in [0,1]$ and ε_1 and ε_2 are independent.

At time 2 the firm is liquidated and debt and equity holders are paid out. Figure 1 depicts the sequence of events.



We assume that all investors are risk neutral and the risk free rate is zero.[6] In addition there are no information asymmetries and all positive NPV projects are adopted. Specifically the first project will commence if $E(F_1) = \mu_1 \geq I$. The condition for starting the second project is

$$E_1(\tilde{F}_2) = \rho F_1 + \mu_2 - \rho\mu_1 \geq I \tag{2.2}$$

And the critical value of the realization of F_1 is:

$$F_1^* \equiv \mu_1 - \frac{\mu_2 - I}{\rho} \tag{2.3}$$

When $F_1 \geq F_1^*$, the second project will be adopted, otherwise it will not be adopted. The comparative static result is then.[7]

Proposition 2.1. *When* $\rho \neq 0$*:*

1. F_1^* *increases with* ρ*:* $\dfrac{\partial F_1^*}{\partial \rho} = \dfrac{\mu_2 - I}{\rho^2}$

2. F_1^* *increases with* μ_1*:* $\dfrac{\partial F_1^*}{\partial \mu_1} = 1$

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[6] We also assume that the firm does not pay dividends at t = 1, with any residual cash flows at t =1 invested by the firm at the risk free rate. We assume that α is independent of F_1 and that all capital goods are depreciated completely after one period.
[7] The proofs for all propositions are contained in the appendix.

3. *F_1^* increases with I:* $\frac{\partial F_1^*}{\partial I} = \frac{1}{\rho} > 0$

This result implies that a firm with a low correlation between current and future projects can sustain a more negative shock to its current project and continue to operate than an otherwise similar firm with a higher correlation. In the following, we are mainly interested in t=1 and consider the situation where the second project will be adopted.

2.1. All Equity Financing

We start by considering the case that any financing needed to undertake the second project is done through equity financing. So the total book and market value of equity are then:

$$\begin{aligned} B_1 &= \max(F_1, \alpha I) \\ M_1 &= \max(F_1 - \alpha I, 0) + E(\alpha F_2) \\ &= \max(F_1 - \alpha I, 0) + \alpha(\mu_2 + \rho(F_1 - \mu_1)) \end{aligned}$$

Let $BM_1 \equiv \frac{B_1}{M_1}$. It is straightforward to show the following:

Proposition 2.2. The effect of ρ on the market value and book-to-market are given by:

$$\frac{\partial M_1}{\partial \rho} = -\alpha(\mu_1 - F_1)$$

$$\frac{\partial BM_1}{\partial \rho} = \alpha \frac{BM_1}{M_1}(\mu_1 - F_1)$$

After a negative shock, $F_1 < \mu_1$. So other things equal, larger ρ corresponds to smaller market value and larger BM value.

Next we consider the change in market and book-to-market value after a negative shock. The time-series results are:

Proposition 2.3 When there is no outside financing need, the effects of changes in F_1 on market value and book-to market are:

$$\frac{\partial M_1}{\partial F_1} = 1 + \alpha\rho$$
$$\frac{\partial BM_1}{\partial F_1} = \frac{\alpha(\mu_2 - \rho\mu_1 - I)}{M_1^2}$$

So a negative shock (lower than expected F_1), always results in a decrease in market value. However, the change in BM depends on the value of ρ. The critical value of *correl* is given by $\rho^* \equiv (\mu_2 - I)/\mu_1$. If $\rho > \rho^*$ smaller F_1 implies an increase in BM, as the traditional argument indicates. But if $\rho < \rho^*$, smaller F_1 implies a *decrease* in BM.

For the situation where necessary outside financing is provided by equity, again the market value always decreases with decreasing F_1. However in this case BM increases monotonically with decreasing F_1.

2.2 Debt Financing

So far we have shown that the change in BM value after a negative earnings shock can be positive or negative depending on the value of *correl*. In this section, we show that the result holds with debt financing. This allows us to consider the situation of financial distress which is the focus of our paper. Importantly, we show that the described effects on BM are strongest for those firms under financial distress.

Let us stress upfront that we do not present an optimal capital structural model here. Thus we will *not* endogenize the choice of debt. While the problem of debt choices can potentially complicate the problem, we emphasize the importance of heterogeneous correlations on the book-to-market value. Furthermore, under our model setup, debt choices do not make (much) difference in terms of project choices. As long as the second project has positive NPV, it will be adopted. The firm issues one-period debt which must be paid off in full at maturity. Otherwise the firm is liquidated. For simplicity, we assume the firm cannot borrow new debt to pay off the old debt. Because of the possibility of default, the face value D_t (t=1, 2) is larger than the issuing price P_{t-1}. In fact, $P_0 = E_0[\min(D_1, F_1)]$.

Again we consider the situation where the firm is not liquidated at t=1. The book value of equity is $B_1 = F_1 - D_1$. To derive the market value, note that the total cash flow at t=2 is:

$$CF_2 = \alpha F_2 + \max(B_1 + P_1 - \alpha I, 0)$$

The second term is the additional cash left after investment in the second project. So the price of the second period debt is $P_1 = E_1[\min(CF_2, D_2)]$. And equity value is given by $M_1 = E_1(CF_2) - P_1$. Given this notation, the default situation is then: $D_2 = CF_2$, which defines:

$$\bar{\varepsilon} = \frac{D_2 - \max(F_1 - D_1 + P_1 - \alpha I, 0)}{\alpha} - (\mu_2 + \rho(F_1 - \mu_1))$$

We denote the associated PDF and CDF as $g(\varepsilon)$ and $G(\varepsilon)$ respectively.

We consider two types of debt choice. In the first the firm maintains a constant face value of debt. The second adopts the more commonly used assumption in which the firm maintains a constant debt to equity ratio. Our results hold for both debt choices, however, for simplicity we present the results for constant face value of debt assumption.

Accordingly, we assume that $D_2 = \alpha D_1$. This defines the situation where the second project scales up by a factor of α and the face value of debt is also scaled up by the same factor. For this situation we have the following:

Proposition 2.4 When there is no extra cash left after the investment, $M_1 = \int_{\bar{\varepsilon}} \alpha(\mu_2 + \rho(F_1 - \mu_1) + \varepsilon - D_1) g(\varepsilon) d\varepsilon$, where $\bar{\varepsilon} = D_1 - (\mu_2 + \rho(F_1 - \mu_1))$. The sensitivities with respect to ρ are:

$$\frac{\partial M_1}{\partial \rho} = -\alpha(\mu_1 - F_1)(1 - G(\bar{\varepsilon}))$$
$$\frac{\partial BM_1}{\partial \rho} = -\frac{BM_1}{M_1}\frac{\partial M_1}{\partial \rho}$$

And the effects of shocks F_1 are:

$$\frac{\partial M_1}{\partial F_1} = \alpha\rho(1 - G(\bar{\varepsilon})) \equiv BM_1^*$$
$$\frac{\partial BM_1}{\partial F_1} = \frac{BM_1^*}{M_1}(BM_1^* - BM_1)$$

The results for debt financing are similar to those for equity financing. Cross-sectionally, larger ρ corresponds to smaller market value and larger BM after a negative shock. Over time, the change in BM depends on *correl.* For low values of *correl* a negative shock to earnings leads to a *decrease* in BM.

The above analysis suggests that the decrease in BM values following a negative shock is unrelated to the financial health of the firm.[8] However, we argue that this is not the case because financially distressed stocks are more likely to suffer a smaller decrease in market value as a result of a negative shock. This result derives from Merton's (1974) model where the equity of a financially distressed firm can be viewed as an at-the-money call option on the firm's assets. In this setting the delta of an at-the-money call option (distressed firm) is smaller than that of an in-the-money option (healthy firm).

[8] We intend to incorporate this part to the model in future versions of this paper.

Furthermore, the negative shock to earnings is likely to increase the volatility of the firm (e.g. Black 1976, Christie 1982, Glosten et al 1993). The increase in volatility results in increased option prices. This effect should be the largest for at-the-money options (distressed firms) as their vega is higher than that of other options. The joint effects of a smaller delta and a larger vega, imply that following a negative shock, financially distressed firm suffer a smaller decrease (or even an increase) in market value, as compared to healthy firms. The book to market of financially distressed firms is therefore more likely to decrease following a negative shock as compared to financially healthy firms.

3. Data and descriptive statistics

3.1 Data

Our data are obtained from three sources: first, stock returns and delisting information are drawn from the CRSP monthly stocks combined files; second, accounting data are retrieved from the COMPUSTAT files: third we use CRSP daily combined files in order to estimate stock volatility. We limit the sample to firms with ordinary common equity outstanding (share codes 10 and 11 in the CRSP files); consequently, ADRs, REITs, and closed-end funds are excluded.

The sample period is July 1975 - June 2004, inclusive. To be included in the sample for year t, a firm must have data on CRSP for both June of year *t* and for December of year *t*-1, COMPUSTAT annual data for year t, and a book value of common equity for year *t* -1. Additionally, we require that all variables necessary to calculate both the O-score and the distance to default for each firm in our sample. The resulting sample consists of 1,150,655 observations of monthly returns that equates to 99,622 firm years. The number of firms delisting from the exchange due to bad performance (delisting codes 400-599) in our sample is 3,314.

3.2 Methodology

We divide the stocks in our sample according to three criteria: size, BM and the financial health of the firm.

Size - Consistent with previous literature we divide all sample stocks into quintiles based on NYSE cut-off points.

Book to Market equity ratio – All stocks with positive BM are independently sorted into equal BM quintiles. We do not censor negative BM stocks from the sample. However, in our initial tests we follow traditional asset pricing literature and report results only for positive BM stocks. Since negative BM stocks are highly distressed firms and are included in our model prediction we include these stocks in later tests in the paper. When negative BM stocks are included in out tests we use the actual BM of the firm rather than the natural log of BM. However, as a robustness check we replicate the main tests in this paper using the natural log of BM – the qualitative results are unaffected by this change.

Financial Health – Similar to Campbell et al (2007) we use two measures of financial health:

a. Ex-post measure – Stocks are defined as financially distressed if they delisted from the exchange due to bad performance or liquidation (delisting codes 400-599) within one year after portfolio formation.

b. Ex-ante Measure – stocks are defined as financially distressed if they belong to the most distressed deciles either according to the EDF model or according to Ohlson's O-score model.[9]

The ex-post measure is straight forward. A stock is defined as financially distressed if it delisted within 12 months after portfolio formation. While this measure obviously involves forward looking it is important because it helps us study the characteristics of stocks that are most likely to be classified as financially distressed stocks. Furthermore, the ex-post measure also helps us to confirm that the characteristics of stocks that are defined as distressed according to the ex-ante measurement are similar to those firms that actually delisted.

There have been two main approaches to measuring the probability of financial distress. Accounting based models such as Altman's Z-score (1968) and Ohlson's O-score (1980) use the financial statements of the firm in order to derive the probability of default. The other approach is market-based and derives the probability of default from market data. A commonly used model is the KMV model (Crosbie and Bohn 2001) which is based on Merton's (1974) seminal work.

Research using accounting based models generally reports that the financially distressed portfolio consists mainly of low BM stocks (Dichev 1998 and Griffin and Lemmon 2002). Conversely, using market based models leads to a distressed portfolio that is mainly composed of high BM stocks. Several recent papers construct a hybrid model that is based both on accounting and market data (Shumway (2001), Chava and Jarrow (2004), Campbell et al. (2007)). Campbell et al. (2007) report that the hybrid model developed in their paper is a better predictor of distress than either type of pure

[9] These models are describer later in the paper.

model. Das et al (2007) find that both accounting and market variables can explain credit default swaps rates.

The above findings suggest that accounting based models are more likely to capture the risk associated with low book-to-market financially distressed (LFD) stocks whereas the market based models are more likely to capture the risk associated with high book-to-market financially distressed (HFD) stocks. Since our interest lies in both types of financial distress we use a hybrid approach to measure the ex-ante definition of financial distress. However, rather than using a model that combines both accounting and market variables we use two pure models (accounting and market based) and define financially distressed firms as those whose stocks are in the most distressed portfolio according to (at least) one of the models. This approach allows us to capture both LFD and HFD stocks into the distressed portfolio while maintaining the separation between market and accounting based models for comparison reasons. For the market based model we use the same specification of the KMV model as Vassalou and Xing (2004).[10] The accounting based model used is Ohlson's O-score model (1980). Thus, at the end of each June of year t all sample stocks are sorted independently according to each model and are allocated into deciles. We define stocks as financially distressed if they belong to the most distressed deciles according to (at least) one of the models. This methodology is referred as the hybrid model. In some tests we use the two models separately in order to investigate the strengths and weaknesses of each pure model.

[10] The value of the assets is equal to the market value of equity plus the book value of the debt. The debt level is assumed to be half of long term debt plus all of current debt. The volatility of assets is computed using the volatility of equity. Accordingly the estimated default frequency (EDF) is derived from the estimated distance to default, which is given by the difference between the value of the assets and debt level normalized by the volatility of the firm assets

3.3 Descriptive statistics

We start our empirical investigation by examining the distribution of financially distressed firms across 25 size/BM portfolios, according to both ex-post and ex-ante definitions. Table I Panel A presents the number of stocks that delisted due to bad performance within a year after portfolio formation (our ex-post definition). Not surprisingly, there is a clear negative monotonic relation between size and actual delisting as 96% of delisted firms belong to the smallest size portfolio prior to delisting. The relation between BM and delisting is U shaped as almost 60% of all delisting firms belong to either the lowest or highest BM quintile.

Table I panel B presents the distribution of financially distressed stocks according to the hybrid model. Of the 16,431 stocks defined as financially distressed, 14,540 have a positive BM. Results show a very similar pattern to that of Panel A. More than 90% of all stocks that are defined as financially distressed belong to the smallest size quintile. Consistent with Panel A results we observe a U shaped relation between BM and financial distress. The proportion of stocks in the two extreme portfolios is 62.7% compared to 58.4% in Panel A. Thus, the hybrid model seems to capture the same size/BM characteristics for financially distressed firms as that captured for firms that subsequently delisted.

In Panel C and D of Table I we examine the average EDF and O-score across 25 size/BM portfolios. Results of panel C show that as expected there is a clear relation between size and EDF. The average EDF of small stocks is more than three times larger than that of the second size quintile and is ten times larger than stocks in the largest quintile. The relation between BM and average EDF is also monotonic. In each size quintile the average EDF is increasing with BM. For example, among small stocks the average EDF for the low BM portfolio is 0.10, whereas for the high BM portfolio it is 0.26. This latter result is consistent with findings reported by Vassalou and Xing (2004).

Table I Panel D presents the average O-score for 25 size/BM portfolios. Note that according to the O-score model higher values represent a higher chance of default. Not surprisingly, and similar to the EDF result, the average O-score results are declining in size. However, the relation between BM and O-score is more complex and depends on size. For large stocks the results are similar to that of the EDF in that there exists a positive monotonic relation between average O-score and BM. However, for small stocks the relation changes to a U shape where the most distressed portfolio is the small low BM portfolio. This result is consistent with previous research (e.g. Dichev 1998 and Griffin and Lemmon 2002).

4. Results

Our model predictions suggest that a negative shock to a firm can result in two different types of financial distress. The first type is associated with stocks with high correlation between the cash flows of current and future projects. The characteristics of these stocks are similar to the usual concept of financially distressed firms: high book to market values, high market leverage and less likelihood of surviving disastrous outcomes. The second type of firm in financial distress is the firm with low correlation and typically high growth opportunities. For these stocks a negative shock to the firm should result in a low BM value and relatively low leverage.

4. 1 Two Types of Financial Distress

Our model suggests that financial distress can take two different forms depending on *correl*. Since *correl* is unobservable we use propositions 2.2 and 2.3 in order to distinguish between the two sub samples of financially distressed stocks. These propositions imply that financially distressed stocks with low (high) correlation will be characterized by low (high) BM. Results of Table I Panels A and B show that according to both the ex-ante and ex-post measurement the relation between financial distress and BM is U shaped. The next test is aimed to investigate the various characteristics of low and high BM financially distressed stocks and whether they are consistent with our model predictions.

Table II Panel A presents the comparison between high and low BM stocks that delist within one year after portfolio formation (ex-post definition). We censor from the sample all stocks that are medium BM stocks (quintiles 2-4). The number of firms in each portfolio is reported in Table I Panel A. There are 722 low BM financially distressed stocks (LFD) and 970 high BM financially distressed stocks (HFD). All differences reported in this section are statistically significant. Rows 1- 4 show that LFD stocks have lower BM (by construction), are younger, and have higher R&D and capital expenditures. Rows 5 and 6 of Table II present the average EDF and O-score respectively. Consistent with previous findings in this paper HFD stocks have higher EDF, whereas LFD stocks have higher O-score.

Rows 7 and 8 examine the leverage of financially distressed firms. Consistent with previous results (Vassalo and Xing 2004) and our model predictions, results in Row 7 show that the market leverage of HFD stocks is much higher than that of LFD stocks

(0.67 to 0.37 respectively). Row 8 presents the book leverage of both types of financially distressed stocks. Our results indicate that the book leverage is slightly larger for LFD stocks than for HFD (0.43 to 0.50 respectively). Further analysis reveals that the dispersion of book leverage of LFD stocks is much larger than of HFD stocks.

Row 9 presents the average market equity at portfolio formation (June of year *t*). The results show that LFD firms are approximately 50% larger than HFD stocks. The average market equity of LFD firms is $36 million compared to only $21 million for HFD firms. The relatively high market value of LFD stocks is a likely explanation as to why market based models under-select these stocks into the distressed portfolio.

Row 10 examines one of the commonly used variables to assess financial health of the firm – net income scaled by total assets (NITA). Results show that NITA is significantly more negative for LFD than for HFD stocks (-0.38 to -0.14 respectively). This result illustrates that accounting based models will tend to pick LFD stocks because this accounting ratio is typically lower for LFD as compared to HFD stocks. We note that the larger losses of LFD stocks are mainly due to scaling by total assets which are typically much lower for LFD than HFD stocks. Campbell et al. (2007) report that scaling net income by market value of total assets (market value of equity plus book value of debt) leads to better prediction of financial distress. They suggest that the more frequent updating of market values of equity may be behind the improved predictive ability. Our findings suggest another potential explanation for the improvement. Scaling by total assets inflate the negative earnings of LFD stocks due to the low book values of these stocks. In contrast, scaling by market value of total assets avoids this bias. Consistent with this explanation, Row 11 reports that the average net income to the market value of assets of LFD stocks and HFD stocks is almost the same (-0.24 to -0.22 respectively).

Panel B presents the results of the same test for stocks that are defined as financially distressed according to the hybrid model. Consistent with findings of Campbell et al (2007) results of both panels are similar.

4.2 The Correlation between Cash Flows of Current and Future Projects

Our main theoretical argument is that the correlation between the cash flows of current and future projects plays a fundamental role in determining the type of financial distress after a negative shock. Our model predicts that firms with low correlation are more likely to have low BM following a negative shock. There are several variables that may affect this correlation. These variables include the similarity between the products of current and future projects, the similarity in technologies being used for both projects, the similarity in the markets that the firm intends to operate for its current and future markets and so on. Results of Table II confirm that LFD and HFD stocks are different in many important characteristics. In this section we examine whether LFD and HFD are related to *correl* as our model predicts or whether low and high BM stocks have essentially different characteristics.

a. direct approach

In this section we attempt to directly estimate the auto-correlation between current and future earnings. A natural way to examine this correlation could be to estimate a time series regression on the earnings for each firm separately, and then examine if stocks with low correlation have low BM and the other characteristics that are predicted by our model. We argue that this approach suffers from two shortfalls. First, since both LFD and

HFD stocks are relatively young (cf. Table II) the time series correlation would be estimated on a small number of observations (Fama and French 2000). Second, estimating a time series regression of earnings is implicitly assuming that the coefficient is unaffected by the negative shock. We argue that this assumption may be problematic because earnings persistence is likely to depend on whether a firm's current projects are succeeding or failing. When current projects are successful the earnings auto-correlation is largely determined by the firm's ability to maintain (or increase) its current success. In these situations the firm is unlikely to make large changes to technologies and strategies that are used for current projects. Conversely, when current projects are failing then the correlation (*correl*) will be largely determined by the ability of the firm to make changes in the technologies and strategies used for current projects.

Therefore, consistent with previous studies (e.g. Freeman et al (1982) Collins and Kothari (1989)) we use cross sectional regression. Since our model assumes that the earnings follow an AR(1) process, we examine the correlation between earnings at time t+1 to earnings at time t. Accordingly we estimate the following regression:[11]

$$NI_{t+1} = \alpha + \rho NI_t + \beta_1 \ln(size)_t + \beta_2 (BM)_t + \beta_3 (BM)_t * NI_t + D\_Years + \varepsilon_{t+1}$$

The important variable is the interaction term between BM and NI. Our model predicts that among financially distressed stocks the coefficient should be positive. The control variables include the firm's BM and size and year fixed affects. The regression is estimated for the entire sample of stocks and separately for financially distressed firms. Results of the regression estimation are presented in Table III.

[11] When the sample is restricted to positive BM stocks we use the natural log of BM in the regression.

Row 1 presents the results for the entire sample of stocks. Results show that earnings persistence is higher among low BM stocks.[12] The coefficient of the interaction variable is negative and significant. All control variables are significant and of their expected sign. Rows 2 and Row 3 present the results for financially distressed firms only. In Row 2 all sample stocks are included and thus we use BM itself. Row 3 contains the results for only positive BM stocks and the natural logarithm of BM is used. Both rows show that in contrast to the results for the entire sample the interaction coefficient is positive and significant. This result suggests, consistent with our model predictions, that among financially distressed stocks the earnings persistence of low BM stocks is lower than that of high BM stocks. However, we note that the result is likely to be affected by survival bias, because the regression estimations include only firms that continue to trade at year t+1.[13] Since stocks that cease trading are likely to be the worst performers both at portfolio formation and prior to delisting it is likely that the autocorrelation of the earnings coefficient is biased downward. Furthermore, it is not clear whether this bias will be equal for LFD and HFD stocks. Thus, we can not exclude the possibility that survival bias may be affecting the interaction variable.

b. Proxies for correl

Results of Table II show that there are large differences in firm characteristics between LFD and HFD stocks. Important differences include that LFD firms are younger, invest more and have larger R&D expenditures than HFD stocks. We argue that these three variables are not simply characteristics of low BM stocks but may serve as a proxy

[12] There have been many papers investigating the predictability of future growth in earnings, profitability and sales etc. However, to the best of our knowledge there has been no direct testing of the relation that links persistence coefficients to book-to-market value.

[13] Of the 14,450 positive BM stocks that are defined as financially distressed, 15% delisted and an additional 11% stopped trading for various reasons.

for the unobserved *correl*. The main explanatory variable we use to proxy for the correlation is the R&D expenditure of the firm scaled by total assets. The reasoning behind our argument is that firms are likely to use their R&D expenditures to alter products and technologies of failing current projects. Chan, Lakonishok and Sougiannis (2001) report that firms with high R&D expenditures are likely to be past losers and that these firms have positive excess returns. They argue that high investment in R&D signals better future prospects. Titman and Wessels (1988), Opler and Titman (1994) and others argue that R&D is a proxy for the specialization of a firm's products. We note that both arguments are not necessarily contradictory as firms with high R&D may indeed specialize in one product but are likely to have the ability to alter it when current projects are failing.

The second variable that we use to proxy for *correl* is the age of the firm. Fama and French (2002) and others note that firms issue in the stock market at an early stage in their life cycle. These early life cycle firms are likely to make large changes as they mature hence *correl* is expected to be relatively low. We note that age can serve also as a control variable to our main variable R&D. Since young firms have larger R&D expenditure it may be that the relation between R&D and a BM is spurious.

The third variable is capital expenditures to total assets. This variable is likely to capture primarily the growth opportunities of the firm. However, it may be that high investing firms are able to make more rapid changes to their investment following the failure of current projects.

The focus of this test is on the difference between the two types of financially distressed firms. Thus, we estimate this regression only for stocks that are defined as financially distressed at portfolio formation.[14] Three additional control variables are added in order to decrease the possibility of a spurious relation: the lagged value of BM, size and the industry BM (of the entire data sample period). The BM control has two important roles. First it verifies that the type of financially distress is not determined solely by the growth opportunities of the firm. Second, it helps to mitigate the problem of accounting conservatism. Chan, Lakonishok and Sougiannis (2001) argue that the fact that accountings rules required R&D expenditures to be treated as an expense rather than an asset causes a systematic bias downward in the BM value of firms that have large R&D expenditures. Therefore, one may argue that the relation between R&D and the type of distress is due to accounting conservatism and not because R&D expenditures proxy for the unobservable correlation. However, since we control for lagged BM values the effect of R&D has already influenced the BM measurement in the previous year. Thus, our findings are largely robust to the effect of conservatism in R&D expenditures. The industry BM control variable is a proxy for growth opportunities in the entire industry and is similar in nature to the variable α in our model. Accordingly we estimate the following Probit regression:

$$LFD_t = \alpha + \beta_1 R\&D_{t-1} + \beta_2 Age_t + \beta_3 Capex_{t-1} + \gamma_1 BM_{t-1} + \gamma_2 Ln(size_{t-1}) + \gamma_3 IndustryBM + \varepsilon_t$$

In order to be included in the test a stock must have a positive book value at portfolio formation and have the other required measures at time t-1. Of the 16,431 firms that are defined as financially distressed 11,216 firms meet this requirement.

[14] As a robustness test we estimate the same regression using the entire sample and estimate it separately on both LFD and HFD stocks. Results are largely consistent with our main findings. The coefficient of R&D is positive when the dependent variable is LFD stocks and negative when the dependant variable is HFD stocks.

Results of this regression are presented in Table IV. Results show that the coefficient on R&D is positive and highly significant regardless of whether it is estimated alone or with the other two variables. This result suggests that firms that have higher R&D are more likely to become LFD after a negative shock. To the extent that R&D expenditure can proxy for the *correl* this result is further supportive evidence for our model predictions. The coefficient on *Age* is negative and significant, suggesting that young firms are more likely to become LFD stocks. The coefficient on *Capex* is positive but insignificant. Further analysis reveals that *Capex* loses its predictive ability when the control for past BM is added suggesting that both variables measure growth opportunities. Of the three control variables both previous BM and industry BM are significant with expected sign. The coefficient of size changes depending on the variable estimated.[15] Finally, as a robustness test we estimate the same regression while limiting the sample to stocks that delist within a year (ex-post definition). Our unreported results show little change in the coefficients.

4.3 The Effect of Negative Shock on BM

The academic literature typically assumes that there is a monotonic relation between financial distress and BM. Fama and French (1992) among others argue that stocks with high BM are more exposed to the financial distress risk factor. On the other side of the spectrum stocks with low BM are considered to be glamour stocks with high growth opportunities. Findings that low BM stocks have on *average* higher profitability than high BM stocks (e.g. Fama and French 1995, Chen and Zhang 1997) are interpreted as being consistent with this view. In contrast, we argue that the relation is not straight

[15] We note that only stocks that are defined as financially distressed are included in this experiment. Therefore, most of the stocks are relatively small which leads to the inconclusive results regarding size. The coefficient on R&D remains positive and highly significant.

forward. Results of Table I show that almost one third of financially distressed firms have low BM. Furthermore, results of Table II show that LFD firms have characteristics that are largely associated with low BM stocks such as high R&D and capital expenditure. This ambiguity is noted is previous research (e.g. Dichev 1998, Griffin and Lemmon 2002). Our model takes the analysis one step further by predicting that following a negative shock the BM of low correlation firms will tend to *decrease*. In essence, our argument is that low BM can proxy for a decrease in current assets and not only for an increase in growth opportunities. Since there is a positive correlation between a decrease in current assets and financial distress it follows that low BM is also a proxy for financial distress. This prediction is contradictory to the common perception of BM which views a decrease in BM as a positive signal for the firm.

The next test is aimed at investigating whether a decrease in BM following negative news is supported in the data. All small stocks are divided to two sub-samples. [16] The first sub-sample consists of stocks that are defined as financially distressed according to the hybrid model at year t, whereas the second consists of all other small stocks.[17] For each of the sub-samples we examine one year transition matrices for BM. Results of this test are reported in Table V Panels A and B. Since our focus is on transition from and into the extreme BM portfolios, for expositional clarity we collapse quintiles 2-4 into one portfolio defined as medium BM. Accordingly, out transitions matrices are 3×3 where each row in Table V presents the BM of the firm one year prior to

[16] The reason we limit our comparison to small stocks is in order to mitigate the size effect. Results of Table I Panel A and B show that more than 90% of all financially distressed firms are part of the smallest size portfolio compared to only 60% in the entire sample. Since our results show that the BM of large stocks is much more persistent than that of small stocks a comparison across all sample stocks may capture the effect of size rather than the effect of financial distress.

[17] As a robustness check we examine the transition matrix of stocks that are defined as financially distressed according to the ex-post definition. Our unreported result shows that the transition matrix is similar to that of Panel A.

portfolio formation (year *t*-1) and each column presents the BM at portfolio formation (year *t*).

Panel A presents the transition matrix for financially distressed stocks. The results show that consistent with our model prediction a *decrease* in BM is often observed among these stocks. For example, the results in Panel A show that 16.4% of medium BM stocks become low BM stocks. This proportion is roughly two and a half times larger than that of healthy stocks as reported in Panel B. Similarly, the move from high to low BM is much more frequent among financially distressed stocks than among healthy stocks (2.7% to 0.4% respectively). These results are consistent with our prediction that a negative shock to earnings often lead to a decrease in BM.

Consistent with the traditional view, financially distressed stocks are also very likely to turn into high BM stocks following a negative shock. Results of Panel A show that 27% of stocks that are part of the medium BM portfolio at year *t* -1 turn into high BM at year *t*. This proportion is twice that of the same transition for healthy stocks. Importantly, our results do not indicate that the BM matrix for financially distressed stocks is systematically less stable than that of healthy stocks. Our results suggest that healthy stocks have a much higher proportion turning from low or high into medium BM stocks. For example, among the healthy stocks sub-sample 44% of the stocks turn from low to medium BM compare to only 31.1% among the distressed sub-sample.

Results of Table V suggest that a negative shock to the company typically results in the company turning into high or low BM. Conversely, healthy stocks are likely to become medium BM. This phenomenon further suggests a U shaped relation between financial distress and BM. The documented decrease in BM after a negative shock has implications for the use of a variable such as Tobin's Q to assess firm performance. An increase in Q value is regarded as a proxy for improvement in the firm performance. However, our findings suggest that among distressed firms this variable is an inadequate measure of firm performance. Indeed, additional untabulated results confirm that there is a U shaped relation between Q values and financial distress. For example, roughly 14% of all financially distressed firms are in the highest deciles of Q value.

Our model predicts that the decrease in BM following a negative shock is not limited to financially distressed stocks but should also be observed, albeit to a lesser degree, among all firms that receive a negative shock. In order to test this prediction all stocks are divided into quintiles based on the percentage change in earning from the previous year. Stocks in the lowest quintile are defined as negative shock portfolio. From this portfolio all financially distressed stocks are censored concentrating on stocks that the negative shock to earnings do not turn them into financially distressed. For these stocks we examine a one year BM transition matrix. Results reported in Panel C are consistent with our model prediction. The proportion of stocks among non-distress negative shock portfolio that turn into low BM stocks is higher than healthy stocks but lower than financially distressed stocks.

Griffin and Lemmon (2002) suggest that investors underestimate the correlation between current and future projects. According to their argument this underestimation mainly affects firms with high growth opportunities, resulting in both low BM and low ex-post realized returns. Conversely, our model suggests that a decrease in BM values after negative shock is likely to happen regardless of the potential mispricing documented in Griffin in Lemmon.

In order to ensure that the decrease in BM is not largely due to mispricing we investigate this phenomenon further. We start by examining the average BM of financially distressed stocks that change from medium to low BM. Our results suggest that these stocks lose more than two thirds of their BM (from 0.68 to 0.20). We argue that this decrease is too large to be explained by mispricing. The next test is aimed at directly examining the possible effect of mispricing on the transition matrix. Griffin and Lemmon report that the underperformance of financially distressed low BM stocks is approximately 0.8% per month compared to the three-factor model. In order to account for this potential mispricing we add 10% to the market value of these stocks at year t.[18] Then, we resort all stocks into BM quintiles using the adjusted market value. Results presented in Table V Panel C confirm our arguments by showing that the transition matrix is hardly affected by the adjustment to market value. For example, the proportion of stocks that transition from medium to low BM changes from 16.4% in Panel A to 16.1% after the adjustment. These findings support our argument that mispricing plays a minor role in the magnitude of the decrease in BM after a negative shock.

4.4 Survivability, Leverage, and Negative BM

Proposition 2.1 of our model suggests that LFD stocks have a higher survival rate than HFD stocks following financial distress. One implication of this proposition is that LFD firms can sustain larger losses before delisting from the stock market. We examine this prediction by comparing NITA of financially distressed stocks prior to delisting. Results of Table II Panel A confirm that on average LFD stocks suffer a greater loss before delisting than HFD stocks. However the univariate analysis may be misleading as other

[18] We note that 10% annually is the upper bound of the mispricing reported is Griffin and Lemmon. {GIL – continue}

factors may influence this result. Specifically, a long line of literature argues that there is a tradeoff between operational and financial risk.[19] The trade-off theory suggests that firms with low (high) leverage will suffer from high (low) losses prior to delisting. Thus, the higher losses of LFD stocks prior to delisting may be driven by low leverage rather than *correl*.

In order to examine this question further we estimate a regression in which the dependent variable is net income to total assets (NITA) of the firm prior to delisting. The main explanatory variable is the BM of the firm. We also include firm age and CAPEX as additional proxies for *correl*. We note that accounting conservatism may play a role in the results because firms with high R&D expenditures are likely to have lower assets values and higher profitability resulting in a downward bias to NITA. We account for this problem by using R&D as a control variable rather than as an explanatory variable. Other control variables include size and industry BM. We first estimate the effect of BM without leverage by performing the following regression:

$$NITA_t = \alpha + \beta_1 BM_t + \beta_2 CAPEX_t + \beta_3 Age_t + \gamma_1 R\&D_t + \gamma_2 Ln(Size)_t + \gamma_3 Ind\_BM_t + \varepsilon_t$$

Results of the regression estimations are presented in Table VI Panel A. Consistent with our model predictions the coefficient of BM is positive and highly significant. The coefficients of CAPEX and Age have their expected signs. All control variable are significant expect for Industry BM.

Next we add market leverage as an additional control variable and re-estimate the regression. Consistent with the trade-off theory the coefficient of leverage is positive and highly significant. The coefficient of BM is still positive and significant although both the

[19] See for example Titman and Wessels (1998), Havokimian, Opler and Titman (2001), Koraczyk and Levy (2003) Kayhan and Titman (2007).

coefficient and t-statistic are roughly reduced by half. This finding seems to suggest that the trade-off theory plays a larger role in determining the profitability of distressed stocks. However, we argue that the effect of *correl* may be non-linear as it is likely to play a key role among low BM stocks. In order to account for this non-linearity effect in BM we add a dummy variable to which we assign the value of 1 if the stock is part of the low BM portfolio. The coefficient on the dummy variable is negative and highly significant. Conversely, the coefficient of BM becomes insignificant. The coefficient of market leverage also reduces but remains highly significant. Therefore, consistent with our model prediction the results presented in Table VI suggest that LFD stocks have a higher survival rate that cannot be explained by differences in leverage or R&D expenditures.

As a robustness check we replace the market leverage by book leverage. Results (not reported) are largely consistent with our previous findings. The coefficient of book leverage is smaller than that of market leverage but still significant. The other major difference is that the coefficient of BM is significant in all regressions.

Another group of stocks that are likely to proxy for high survivability is the subset of stocks with negative BM. Negative BM stocks lose the entire book value of equity and yet continue to trade. These stocks are typically excluded from any analysis (Fama and French 1992).[20] Our model prediction suggests that these stocks resemble LFD stocks though they are more financially distressed. The proportion of negative BM stocks in our sample is 2.6%. As expected, negative BM stocks represent the most distressed portfolio. The proportion of negative BM stocks among delisted firms is 12.5% almost five times

[20] Campbell et al. (2007) treat negative BM stocks as low BM stocks. They replace the original negative book value with $1.

larger than their overall proportion. Negative BM stocks also have larger average EDF and O-score than all other size BM portfolios (0.347 and 3.990 respectively).[21]

Our focus is on stocks that turn from positive into negative BM. There are a total of 953 cases in the sample period. According to our model predictions these stocks should have the attributes of low *correl* stocks: they should be young firms with low BM and high R&D and CAPEX. We estimate the following Probit regression:

$$NEG_t = \alpha + \beta_1 R\,\&\,D_{t-1} + \beta_2 Capex_{t-1} + \beta_3 Age_{t-1} + \beta_4 BM_{t-1} + \gamma_2 Ln(size_{t-1}) + \gamma_3 IndustryBM + \varepsilon_t$$

where NEG_t is a dummy variable which is assigned the value of 1 if the stock becomes a negative BM stock. Other variables are as defined in Panel A.

Consistent with the methodology used in Panel A we first estimate the regression as specified above. We then add a leverage and finally add a low BM dummy to account for possible non-linearity in BM effect.

Results for this regression estimation are reported in Table VI Panel B. Consistent with our model predictions all variables that are assumed to be correlated with *correl* have their expected sign and are significant. The only exception is firm age in Row 1 which is insignificant. Interestingly, the coefficient of market leverage is positive and highly significant. This suggests that firms with high leverage are more likely to become negative BM stocks. A possible explanation for this finding is that part of the value for distressed stocks is due to deviations from absolute priority rules (e.g. Warner (1977) and Eberhart et al. (1990)). Thus, it may be that firms with high debt are able to extract most of the value and thus survive longer. The fact that all other variables become more

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[21] Hussain et al (2002) examine negative BM stocks and report that these stocks earn very low returns of the same magnitude as the risk free rate.

significant once leverage is added to the regression also suggests that two different factors are likely to affect results.

5. Implications - Predictive Ability

The results of Table I suggest that the EDF model assigns a higher default frequency to stocks with higher BM. Conversely, the O-score assigns a higher delisting probability to stocks with a low BM ratio.

The next test examines the predictive power of both models with respect to delisting probability. Our aim is not to conduct a horse race between the two models but rather to learn about their strength and weaknesses. We define distressed stocks as stocks that belong to the highest deciles (most distressed) according to each model. The focus of this test is to examine ability of each model to predict delisting among three portfolios of BM (low, high and negative). We use two measures in this test. The first examines the ability of the model to select delisting firms into the distressed portfolio (Shumway 2001, Bharath and Shumway 2004), so that:

$$M_1 = \frac{\textit{Number of stocks that belong to the distressed portfolio and subsequently delist}}{\textit{Total number of stocks that delist and belong to that portfolio}}$$

The second measure examines the accuracy of the model in selecting stocks into the distressed portfolio. This measurement is calculated as the ratio of the number of stocks from each portfolio that are selected by the model and that delisted within a year divided by the total number of stocks from that portfolio that are selected into the distressed portfolio.

$$M_2 = \frac{\textit{Number of stocks that belong to the distressed portfolio and subsequently delist}}{\textit{Total number of stocks that are selected to the distressed portfolio}}$$

Note that while in the overall sample a model that is better according to M_1 will necessarily be better according to M_2. However, this is not necessarily true for sub-samples due to the fact that different models will select a differing number of stocks into each sub-sample.

Table VII Panel A presents the results for of the measures M_1 and M_2 for the EDF and O-Score models. Row 1 reports the ability of each model to predict delisting for the entire sample. Consistent with results from default research (e.g. Hillegeist et al. 2004) results in Row 1 show that overall the ability of the EDF model to predict delisting is better than that of the O-score model (52.4% to 47.1% respectively).

Next, we examine the ability of each model to predict delisting for HFD and LFD stocks separately. Row 2 reports M_1 values for HFD stocks. Results show that the EDF model does a much better job in predicting delisting probabilities than the O-score model. Almost two thirds of HFD stocks that delist are selected by the EDF model into the most financially distressed portfolio compared with only around one quarter for the O-score model. Conversely, Row 3 shows that among LFD stocks the situation is reversed with the EDF model selecting less than 40 percent of the stocks that delisted to the distressed portfolio compared with over 70 percent for the O-score model. The last row presents the ability of each model to predict delisting for negative BM stocks. Not surprisingly, both models select a large proportion of negative BM stocks that subsequently delisted into the distressed portfolio. Results show that the O-score out- performs the EDF model by selecting 81 percent into the distressed portfolio compared to 67 percent by the EDF model. Since the O-score model has been shown to have a better ability to pick LFD stocks, this finding further confirms our model predictions that negative BM stocks are largely LFD stocks.

The last three columns of Table VII present the results for the accuracy measurement (M_2). In all sub-samples the results of the accuracy measurement are opposite to that of the selecting measurement. This result suggests that both models do not select the correct proportions of LFD and HFD stocks into the distressed portfolio. For example the EDF model under selects LFD stocks into the distressed portfolio. As a result the model selects only extreme distressed stocks into the distressed portfolio. This will result in lower M_1 for the EDF model among LFD stocks. However, the accuracy measurement will be high as only very distressed LFD are selected by the model.

Panel B of Table VII compares the predictive ability of our hybrid model to the two pure models. This comparison is of interest since the hybrid model uses the same methodology as the two pure models. Thus, differences in predictive ability are likely to be due to an unbalanced selection between HFD and LFD of each of the pure models.[22] Results are consistent with this argument by showing that the ability of the hybrid model to predict delisting is 3.4% better that that of the EDF model. Most of the difference is due to the hybrid model being able to predict delisting better than the EDF model for LFD stocks.

[22] The hybrid model selects a larger number of stocks into the distressed portfolio than either of the pure models - 16.5% compared to 10%. In order to overcome this bias we increase the number of stocks selected by the pure models to match that of the hybrid model. As a robustness check we reduce the number of stocks selected by the hybrid model to 10%. This approach leads to similar results.

6. Conclusions

In this paper we examine the effect of financial distress on stock characteristics. We develop a theoretical model that predicts that the outcome from a negative shock to the cash flows of a firm is sensitive to the correlation between the cash flows of current and future projects. For firms with high correlation financial distress will lead to a large decrease in market value. Hence, these firms are less likely to survive disastrous outcomes for current projects. Conversely, the market value of firms with low correlation is less affected by the failure of current projects. These firms are likely to suffer a decrease in their BM that is derived from a decrease in book values. However, since the present value of growth opportunities is hardly affected these firms can survive a disastrous outcome for current projects and still continue to trade.

Our model and empirical results provide an explanation for the differing ability of accounting versus market based models to predict financial distress. Market models that are based on changes in the stock price are more likely to select high correlation stocks into the distressed portfolio because these stocks react strongly to a negative shock. On the other hand, accounting models are likely to pick low correlation stocks as they can sustain heavier losses and still continue to trade. Using these differences we are able to explain many of the results that have been previously reported in the literature.

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Table I

Descriptive Statistics of 25 Portfolios Sorted by Size and Book-to-Market Ratio detailing probability to delist and default average estimated distance from default and O-score and proportion of financially distressed stocks

This table presents summary statistics for 25 size/BM portfolios. At the end of each June of year t during the period 1975-2004 all common stock are sorted into market capitalization quintiles based on NYSE cutoff points. Then stocks are independently sorted to BM quintiles. Book-to-market ratio is defined as in Fama and French (1992) - the book value of the equity at the end of year t-1, divided by the market value of the firm on the last trading day of December in year t-1. We use two different models in order to estimate the financial health of the firm. The first model is the KMV model that is based on option pricing theory. At the end of each June we estimated the value of the assets of the firm and measure its distance from a critical debt level, calculated as half of the long term debt plus all current debt. We normalize this distance by the volatility of the assets which is estimated using past volatility of stock prices. This distance to default is then converted to an expected default frequency. The second model is the O-score model that is based on accounting ratios. At each June we calculate for each firm the O-score based on accounting data of the previous year. To reduce the influence of outliers on the other estimated accounting ratios, the smallest and largest 0.5% of the observations are set equal to the next largest or smallest values in the respective sample.

In Panel A we use the exp-post measure. That is, we calculate the number of stocks that stop trading on the exchange either because they liquidated (delisting codes 400-499) or were delisted from the exchange due to bad performance (delisting codes 500-599). Each cell in the table presents the number of stocks that delisted in the corresponding size/BM portfolio. The number in parenthesis is the proportion of stocks that delisted in each portfolio out of the total number of delisted stocks in our sample.
Panel B present the distribution of stocks that are defined as financially distressed. We use a hybrid model that is based on both the EDF and the O-score models in order to determine the financial health of the firm. At the end of each June all stocks are independently sorted according to both models. Stocks that are in the most distressed deciles according to either model are defined as financially distressed. There are total of 16,431 stocks that are defined as financially distressed according to the hybrid model (16.5% of all stocks). Of this number 14,540 have a positive BM.
Panel C presents the expected default frequency. At the end of each June we calculate the expected default frequency for the entire sample stocks. Then for each of the 25 size/BM portfolio we calculate the average EDF.
Panel D presents the average O-score for each of the 30 size/BM portfolios. The O-score model is defined as follows:

$$-1.32 - 0.407\log(total\,assets) + 6.03\frac{total\,liabilities}{total\,assets} - 1.43\frac{working\,capital}{total\,assets} + 0.076\frac{current\,liabilities}{total\,assets}$$

$$-1.72\ (\text{1 if total liabilities} < \text{total assets, else 0}) - 2.37\frac{\text{net income}}{\text{total assets}} - 1.83\frac{funds\,from\,operation}{tatal\,liabilities}$$

$$+\ 0.285\ (\text{1 if net loss for the last two years, else 0}) - 0.521\frac{net\,income_t - net\,income_{t-1}}{|net\,income_t| + |net\,income_{t-1}|}.$$

Panel A: (Ex-post measure)						
	Book to market					
Size	1	2	3	4	5	Total
Small	685	376	344	425	950	2780
	(23.63)	(12.97)	(11.87)	(14.66)	(32.77)	(95.90)
2	21	11	6	14	13	65
	(0.72)	(0.38)	(0.21)	(0.48)	(0.45)	(2.24)
3	10	8	9	5	5	37
	(0.34)	(0.28)	(0.31)	(0.17)	(0.17)	(1.28)
4	4	5	1	1	2	13
	(0.14)	(0.17)	(0.03)	(0.03)	(0.07)	(0.45)
Large	2	2	0	0	0	4
	(0.07)	(0.07)	(0.00)	(0.00)	(0.00)	(0.14)
Total	722	402	360	445	970	2899
	(24.91)	(13.87)	(12.42)	(15.35)	(33.46)	(100)

Panel B: Hybrid model						
	Book to market					
Size	1	2	3	4	5	Total
Small	3638	1650	1561	1812	4650	13311
	(25.02)	(11.35)	(10.74)	(12.46)	(31.98)	(91.55)
2	329	106	67	76	233	811
	(2.26)	(0.73)	(0.46)	(0.52)	(1.60)	(5.58)
3	96	28	35	28	92	279
	(0.66)	(0.19)	(0.24)	(0.19)	(0.63)	(1.92)
4	31	13	17	13	29	103
	(0.21)	(0.09)	(0.12)	(0.09)	(0.20)	(0.71)
Large	19	2	4	6	5	36
	(0.13)	(0.01)	(0.03)	(0.04)	(0.03)	(0.25)
Total	4113	1799	1684	1935	5009	14540
	(28.29)	(12.37)	(11.58)	(13.31)	(34.35)	(100)

Panel C: Option based model expected default frequency						
	Book to market					
Size	1	2	3	4	5	Total
Small	0.10	0.10	0.11	0.12	0.26	0.15
2	0.03	0.03	0.03	0.05	0.15	0.05
3	0.02	0.02	0.02	0.03	0.10	0.03
4	0.01	0.01	0.02	0.02	0.07	0.02
Large	0.01	0.01	0.01	0.01	0.02	0.01
Total	0.06	0.05	0.07	0.09	0.23	0.10

Panel D: O-Scores (Accounting based model)						
	Book to market					
Size	1	2	3	4	5	Total
Small	1.34	-0.29	-0.50	-0.45	-0.17	-0.05
2	-1.23	-1.79	-1.54	-1.24	-1.14	-1.43
3	-2.09	-2.05	-1.67	-1.34	-1.48	-1.79
4	-2.45	-2.16	-1.76	-1.48	-1.51	-1.97
Large	-2.68	-2.42	-2.08	-1.85	-1.93	-2.32
Total	-0.36	-1.23	-1.07	-0.80	-0.41	-0.77

Table II

Characteristics of Low and High BM Financially Distressed Firms

This table compares the characteristics of low BM financially distressed stocks (LFD) and high BM financially distressed stocks (HFD). We define financial distress according to both our ex post and ex-ante definitions (panel A and B respectively). Since our focus is on the differences between LFD and HFD stocks we censor all median BM stocks (quintiles 2-4).To reduce the influence of outliers the smallest and largest 1% of the observations are set equal to the next largest or smallest values in the respective sample. Row 1 presents the average BM at portfolio formation. Row 2 presents the average age in years. Rows 3 and 4 present R&D expenditures to total assets and capital expenditure to total assets respectively. Row 5 presents the average expected default frequency whereas Row 6 presents the average O-score. Rows 7 and 8 present the market leverage and book leverage respectively. Row 9 presents the average market value. Row 10 (11) presents the ratio of net income to total (market) assets.

Panel A compares the characteristics of stocks that delisted one year after portfolio formation. At the end of each June stocks are sorted according to BM. Only stocks that delisted due to bad performance (delisting codes 400-599) within one year after portfolio formation are included in the analysis.

In Panel B we sort all stocks independently according to EDF model and the O-score model. Stocks that are in the most distressed deciles in (at least) one of the models are defined as financially distressed.

A *, **, *** denotes significance at the 5%, 1%, 0.1% respectively.

Panel A: Firms that Delisted Within One Year after Portfolio Formation (ex-post definition)

		LFD	HFD	Difference
(1)	Book to Market	0.17	4.61	-4.45***
(2)	Age (in years)	3.43	6.13	-2.69***
(3)	R&D to Total Assets	0.082	0.018	0.065***
(4)	Capex to Total Assets	0.090	0.063	0.027***
(5)	EDF	0.34	0.58	-0.23***
(6)	O-score	4.12	1.45	2.67***
(7)	Market Leverage	0.26	0.63	-0.37***
(8)	Book Leverage	0.50	0.43	0.08***
(9)	Market Value[a]	36.02	21.36	14.66**
(10)	Net Income to Total Assets	-0.38	-0.13	-0.29***
(11)	Net Income to Total Market Assets	-0.24	-0.22	-0.02

Panel B: Firms that are Defined as Financially Distressed according to The Hybrid Model (ex-ante definition)

		LFD	HFD	Difference
(1)	Book to Market	0.17	6.58	-6.41***
(2)	Age (in years)	3.56	5.42	-1.86***
(3)	R&D to Total Assets	0.132	0.019	0.113***
(4)	Capex to Total Assets	0.086	0.066	0.199***
(5)	EDF	0.21	0.61	-0.40***
(6)	O-score	4.56	0.92	3.64***
(7)	Market Leverage	0.21	0.72	-0.50***
(8)	Book Leverage	0.48	0.47	0.01
(9)	Market Value[a]	73.82	47.63	26.19***
(10)	Net Income to Total Assets	-0.41	-0.09	-0.32***
(11)	Net Income to Total Market Assets	-0.16	-0.13	-0.03***

[a] – In order to control for outliers in the delisting sample the highest 0.5% of market value are set equal to the 99.5% respectively.

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Table III

Earnings Persistence among Financially Distressed Stocks.

This table presents the earnings persistent among the entire sample and financially distressed stocks. At the end of each June stocks that are in the top deciles according to the EDF model or the O-score model are defined as financially distressed stocks whereas the rest of the stocks are defined as financially healthy. We estimate the following linear regression for both the entire sample and for financially distressed stocks separately:

$$(1)\ NI_{t+1} = \alpha + \rho NI_t + \beta_1 \ln(size)_t + \beta_2 \ln(BM)_t + \beta_3 \ln(BM)_t * NI + D\_Years + \varepsilon_{t+1}$$

where

NI_{t+1} – Net Income of the firm a year after portfolio formation.
NI_t – Net income of the firm at portfolio formation.
$Ln(size)_t$ – The natural logarithm of the market value of the firm at portfolio formation.
$Ln(BM)_t$ – The natural logarithm of the BM of the firm at portfolio formation.
D_years – Matrix that controls for year fixed effects.

Row 1 presents the regression estimation for the entire sample. Row 2 presents the same regression estimation for stocks that are defined as financially distressed. Row 3 presents the regression estimation for positive BM financially distressed stocks using the natural logarithm of BM.

In order to control for outliers in each regression estimations the lowest and highest 1% set equal to the 1% and 99% respectively.

		NI	BM	Ln(Size)	BM*NI
(1)	Entire sample	0.807*** (0.002)	4.572*** (0.311)	9.057*** (0.172)	-0.012*** (0.001)
(2)	Financially distressed only (including negative BM)	0.467*** (0.011)	1.814*** (0.287)	-0.050 (1.510)	0.045*** (0.004)
(3)	Financially distressed only (positive BM and ln)	0.481*** (0.011)	4.300*** (0.462)	-0.374 (0.527)	0.057*** (0.004)

Table IV
Probit Estimates of the Probability of Firm being LFD after a Negative Shock

This table examines the probability of a firm being in the lowest BM quintile after receiving a negative shock. We include in our analysis only stocks that are defined as financially distressed according to the hybrid model. For these stocks we run the following Probit regression:

$$LFD_t = \alpha + \beta_1 R\,\&\,D_{t-1} + \beta_2 Age +_t \beta_3 Capex_{t-1} + \gamma_1 BM_{t-1} + \gamma_2 Ln(size_{t-1}) + \gamma_3 IndustryBM + \varepsilon_t$$

LFD – is a binary variable to which the value of 1 is assigned if the stock is part of the lowest BM when defined as financially distressed.
R&D – is the research and development expenses scaled by the total assets of the firm
CAPEX is the capital expenditure of the firm scaled by total assets
Age – is the difference between the month of portfolio formation and the first month that the firm started to trade
BM – is the book to market of the firm
IndustryBM –is the total book value of the industry (4-digit SIC code) divided by the total market value
There are 11,216 firms that are included in our final sample of which 2,880 are LFD stocks. Numbers in the table are the coefficients estimates while numbers in brackets present the standard errors of the coefficients.
A *, **, *** denotes significance at the 5%, 1% and 0.1% levels respectively.
In order to control for outliers in each regression estimations the lowest and highest 1% set equal to the 1% and 99% respectively.

Intercept	R&D $_{t-1}$	Age$_t$	Capex$_{t-1}$	BM$_{t-1}$	LnSize$_{t-1}$	Ind_BM
0.020	2.208***			-0.698***	-0.040***	-0.080**
(0.041)	(0.120)			(0.021)	(0.009)	(0.024)
0.177***		-0.021***		-0.761	-0.007	-0.143***
(0.042)		(0.003)		(0.021)	(0.009)	(0.024)
0.216***			-0.155	-0.744***	0.001	-0.147***
(0.041)			(0.149)	(0.021)	(0.009)	(0.024)
0.056	2.190***	-0.016***	0.128	-0.705***	-0.032**	-0.082**
(0.044)	(0.122)	(0.003)	(0.153)	(0.021)	(0.010)	(0.024)

Table V
One-Year Transition Matrix of BM for Small Stocks

This table presents the one year transition matrix of BM for small stocks. At the end of each June of year t-1 stocks are allocated into three BM portfolios: Low (lowest BM quintile) Medium (quintiles 2-4) and High (highest quintile). Then, for each stock examine its BM in the following June (year t). We censor from the sample all stocks that do not have a *positive* BM ratio in both consecutive years. Rows in the tables represent the BM at year t-1 whereas the columns represent the BM in the current year (year t).

Panel A presents the transition matrix for small stocks that are defined as financially distressed according to either the EDF model or the O-score model (the hybrid model). Stocks are defined as financially distressed if they belong to the most distressed decile according to either model. The resulting sample consists of 7,909 stocks.

Panel B presents the one year book to market transition matrix for the healthy small stocks. We define healthy stocks as stocks that are not defined as financially distressed according to both ex-ante and ex-post definitions. There are 35,354 stocks that are included in the resulting healthy small stock sample.

Panel C present the transition matrix for stocks that suffer from negative earnings shock but are not financially distressed. Each year all stocks are sorted to quintiles according to their percentage change in net income. Stocks in the lowest quintile are defined as suffering from negative earnings shock.

Panel D presents the one year book to market transition matrix of stocks that are defined as financially distressed. In this panel the market value is adjusted in order to account for the possible mispricing reported in previous research. The adjustment is done by adding 10% by value to the market value of financially distressed stocks. Note that 10% has been shown to be an upper limit to the mispricing of LFD stocks.

Panel A: Transition matrix for financially distressed stocks (ex-ante definition)

	Book to Market (year t)		
BM (year t-1)	Low	Medium	High
Low	65.6	31.1	3.3
Medium	16.4	56.6	27.0
High	2.7	19.1	78.2

Panel B: Transition matrix for healthy small stocks

	Book to Market (year t)		
BM (year t-1)	Low	Medium	High
Low	55.4	44.0	0.7
Medium	5.9	80.4	13.7
High	0.4	27.1	72.6

Panel C: Transition matrix for negative shock stocks that are not financially distressed

	Book to Market (year t)		
BM (year t-1)	Low	Medium	High
Low	67.7	31.1	1.1
Medium	9.7	74.7	15.6
High	0.2	30.6	69.1

Panel D: Transition matrix for financially distressed stocks after controlling for possible mispricing

	Book to Market (year t)		
BM (year t-1)	Low	Medium	High
Low	63.6	33.1	3.3
Medium	16.1	57.3	26.5
High	2.6	20.8	76.6

Table VI
Survivability of Financially Distressed Firms

In this table we examine the survivability of financially distressed firms. First, in Panel A we estimate the last recorded net income to total assets (NITA) of the firm prior to delisting. We include in the sample only firms that delisted within one year after portfolio formation (ex-post definition). We censor from the sample all negative BM stocks and stocks that do not have a BM or other variables in the previous year. The resulting sample consists of 2,236 stocks.
We estimate the following regression:

$$NITA_t = \alpha + \beta_1 BM_t + \beta_2 CAPEX_t + \beta_3 Age_t + \gamma_1 R\&D_t + \gamma_2 Ln(Size)_t + \gamma_3 IndustryBM_t + \varepsilon_t$$

where NITA is the net income to total assets at portfolio formation, leverage is the ratio between the book value of debt divided by sum of the market value of equity and book value of debt. Low BM is a dummy variable to which we assign the value of 1 if the stock is the lowest quintile of BM. All the rest of the variables are defined in the same manner as throughout the paper.
In Panel B This panel presents the probability of the firm to turn from positive BM to negative BM stocks. We include in our analysis only stocks that have a positive BM in the previous year. For these stocks we ran the following Probit regression:

$$NEG_t = \alpha + \beta_1 R\&D_{t-1} + \beta_2 Capex_{t-1} + \beta_3 Age_{t-1} + \beta_4 BM_{t-1} + \gamma_2 Ln(size_{t-1}) + \gamma_3 IndustryBM + \varepsilon_t$$

NEG_t is a binary variable to which the value of 1 is assigned if the stock becomes a negative BM stock. All other variables are estimated in the same manner as throughout this paper
There are 82,566 firms that are included in our final sample of which 953 turn into negative BM stocks. Numbers in the table are the coefficients estimates while numbers in brackets present the standard errors of the coefficients. In order to control for outliers in each regression estimations the lowest and highest 1% set equal to the 1% and 99% respectively.
A *, **, *** denotes significance at the 5%, 1%, 0.1% respectively

Panel A: Regression estimation for NITA prior to delisting					
BM	Capex	Age	R&D	Leverage	Low BM
0.007***	-0.143**	0.006***	-1.362***		
(0.001)	(0.051)	(0.001)	(0.043)		
0.004**	-0.157**	0.005***	-1.266***	0.135***	
(0.001)	(0.050)	(0.001)	(0.044)	(0.017)	
0.002	-0.101*	0.004***	-1.214***	0.090***	-0.125***
(0.001)	(0.05)	(0.001)	(0.044)	(0.017)	(0.011)
Panel B - Probit estimates for the probability of a firm becoming negative BM					
BM	Capex	Age	R&D	Leverage	Low BM
-0.040***	0.774***	-0.002	1.819***		
(0.008)	(0.152)	(0.002)	(0.119)		
-0.072***	0.793***	-0.008***	2.983***	1.468***	
(0.008)	(0.161)	(0.001)	(0.129)	(0.063)	
-0.055***	0.442**	0.004***	2.340***	1.796***	0.870***
(0.007)	(0.163)	(0.001)	(0.130)	(0.067)	(0.035)

Table VII
Predictive ability of EDF, O-score and Hybrid model. for LDF, HDF and Negative BM Portfolios

This table compares the ability of the EDF, O-Score and hybrid models to predict delisting. In Panel A the EDF and O-Score models are examined. At the end of each June all sample stocks are sorted independently into deciles of financial health according to the O-score model and the EDF model. Stocks in the highest (most financially distressed) deciles according to each model are defined as financially distressed whereas stocks from all other deciles are defined as healthy stocks. We use two measures of prediction ability. The first examines the ability of the model to select delisted stocks into the distressed portfolio. We calculate it as the ratio of the number of stocks that delisted and belonged to the most distressed portfolio to the total number of stocks that delisted (delisting codes 400-599) so that:

$$M_1 = \frac{Number\ of\ stocks\ that\ belong\ to\ the\ distressed\ portfolio\ and\ subsequently\ delist}{Total\ number\ of\ stocks\ that\ delist\ in\ that\ portfolio}$$

The second measure examines the accuracy of the model in picking distressed stocks. It is calculated as the ratio of the number of stocks that are selected into the distressed portfolio and delisted within a year to the total number of stocks that are selected into the distressed portfolio.

$$M_2 = \frac{Number\ of\ stocks\ that\ belong\ to\ the\ distressed\ portfolio\ and\ subsequently\ delist}{Total\ number\ of\ stocks\ that\ are\ selected\ to\ the\ distressed\ portfolio}$$

We examine the prediction ability first among all sample stocks (row 1), then separately among HFD and LFD stocks (rows 2 and 3). Finally, we examine the prediction ability among negative BM stocks (row 5). In Panel B the hybrid model is examined by calculating the same ratios. In our hybrid model stocks are defined as financially distressed if they are in the lowest deciles of the EDF model or the O-score model Our hybrid model define 16,431 (16.5%) of stocks as financially distressed. In order to compare between the O-score and EDF models and the hybrid model we calculate M_1 for each model and then calculate the differences between the hybrid model and the EDF model and the hybrid model and the O-Score model.

Panel A: The pure models (EDF and O-Score)

		Ability to select (M_1)			Accuracy (M_2)		
		EDF	O-score	Difference	EDF	O-score	Difference
(1)	Overall (n=3314)	52.4%	47.1%	5.3%***	17.4%	15.7%	1.7%***
(2)	HFD (n=970)	64.0%	25.9%	37.9%***	13.7%	19.1%	-5.4%***
(3)	LFD (n=722)	38.4%	70.5%	-32.1%***	25.5%	13.5%	12.0%***
(4)	Negative (n=415)	67.2%	81.0%	-13.7%***	31.5%	23.9%	7.6%***

Panel B: Comparison of EDF and O-Score models with the hybrid model

		C1	C2	C3	Differences	
		Hybrid	EDF	O-score	C1 – C2	C1 – C3
(1)	Overall (n=3314)	71.0%	67.5%	66.5%	3.4%***	4.4%***
(2)	HFD (n=970)	68.4%	78.7%	49.5%	-10.2%***	18.9%***
(3)	LFD (n=722)	78.1%	53.2%	84.1%	24.9%***	-6.0%***
(4)	Negative (n=415)	93.7%	78.3%	93.0%	15.4%***	0.7%

Appendix

Proposition 2.1: *When* $\rho \neq 0$ *:*

1. F_1^* *increases with* ρ*:*

$$\frac{\partial F_1^*}{\partial \rho} = \frac{\mu_2 - I}{\rho^2} \geq 0$$

2. F_1^* *increases with* μ_1*:*

$$\frac{\partial F_1^*}{\partial \mu_1} = 1$$

3. F_1^* *increases with I:*

$$\frac{\partial F_1^*}{\partial I} = \frac{1}{\rho} > 0$$

The above inequalities derive from the assumptions that $\mu_2 \geq I$ (first result) and $\rho \in (0,1]$ (third result).

We consider all-equity financing first, which gives rise to:

$$\begin{aligned} B_1 &= \max(F_1, \alpha I) \\ M_1 &= \max(F_1 - \alpha I, 0) + E(\alpha F_2) \\ &= \max(F_1 - \alpha I, 0) + \alpha(\mu_2 + \rho(F_1 - \mu_1)) \end{aligned}$$

Let $BM_1 \equiv \frac{B_1}{M_1}$.

Proposition 2.2. The effect of ρ on the market value and book-to-market are given by:

$$\frac{\partial M_1}{\partial \rho} = -\alpha(\mu_1 - F_1)$$

$$\frac{\partial BM_1}{\partial \rho} = \alpha \frac{BM_1}{M_1}(\mu_1 - F_1)$$

After a negative shock, $F_1 < \mu_1$. So other things equal, larger ρ corresponds to smaller market value and larger BM value.

Proof:

Set, $F_1 > \alpha I$ and differentiate M_1 and BM_1 with respect to ρ.

Next set $F_1 \leq \alpha I$ and differentiate M_1 and BM_1 with respect to ρ. The result follows.

Proposition 2.3 When there is no outside financing need, the effects of changes in F_1 on market value and book-to market are:

$$\frac{\partial M_1}{\partial F_1} = 1 + \alpha\rho > 0$$
$$\frac{\partial BM_1}{\partial F_1} = \frac{\alpha(\mu_2 - \rho\mu_1 - I)}{M_1^2}$$

Proof:

Set, $F_1 > \alpha I$ and differentiate M_1 and BM_1 with respect to F_1. Clearly $1+\alpha\rho$ >0 because of assumptions on α and ρ.

The critical value of *correl* is derived by setting $\frac{\partial BM_1}{\partial F_1}$=0 and is given

by $\rho^* \equiv (\mu_2 - I)/\mu_1$. If $\rho > \rho^*$ smaller F_1 implies an *increase* in BM. If $\rho < \rho^*$, smaller F_1 implies a *decrease* in BM.

Now assume debt financing where $D_2 = \alpha D_1$**.** This defines the situation where the second project scales up by a factor of α and the face value of debt is also scaled up by the same factor. For this situation we have the following:

Proposition 2.4 When there is no extra cash left after the investment,

$M_1 = \int_{\bar{\varepsilon}} \alpha(\mu_2 + \rho(F_1 - \mu_1) + \varepsilon - D_1) g(\varepsilon) d\varepsilon$, where $\bar{\varepsilon} = D_1 - (\mu_2 + \rho(F_1 - \mu_1))$. The sensitivities with respect to ρ are:

$$\frac{\partial M_1}{\partial \rho} = -\alpha(\mu_1 - F_1)(1 - G(\bar{\varepsilon}))$$

$$\frac{\partial BM_1}{\partial \rho} = -\frac{BM_1}{M_1}\frac{\partial M_1}{\partial \rho}$$

And the effects of shocks F_1 are:

$$\frac{\partial M_1}{\partial F_1} = \alpha\rho(1 - G(\bar{\varepsilon})) \equiv BM_1^*$$

$$\frac{\partial BM_1}{\partial F_1} = \frac{BM_1^*}{M_1}(BM_1^* - BM_1)$$

Proof:

Use Leibnitz' theorem.