# Book to Market, Turnaround Probability and Stock Returns

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**Abstract**

Book to market (BM) has long been associated with growth opportunities. We argue that after a negative shock to earnings, the BM of the firm is mainly determined by the short-term recovery ability of the firm. Firms that have high (low) probability to recover from a negative shock will have low (high) BM after a negative shock. We confirm this relation both analytically and empirically and show that differences in growth opportunities are unlikely to explain our results. We also find that firms with high probability of successful turnaround have extremely low return. Heterogeneity in turnaround probability can also serve as an explanation to previous empirical findings.

*JEL Classification: G10, G33*

## 1. Introduction

Since the seminal work of Fama and French (1992, 1993) the book to market equity ratio (BM) of the firm has been used extensively to predict stock returns. Yet, there is still disagreement whether this relation is because of risk or mispricing (e.g., Fama and French (1993), Lakonishock et al. (1994)). A recurring finding is that the value effect is higher among firms with negative attributes. For example, larger value spreads are reported for both stocks that have weak accounting performance (Griffin and Lemmon (2002), Novi-mark (2012)) and weak market performance (Asness (1997) and Daniel and Titman (1999)). This result is typically driven by very low returns of the portfolio that are in the intersection between negative attributes and high growth opportunities.[1] To date, mainly behavioral explanations are offered for this phenomenon.

In this paper we investigate the performance of firms after they receive a negative shock to earnings. We argue that the BM of these firms is largely driven by the short-term ability of the firm to recover from the negative shock. Firms that have high probability to successfully turnaround their operations are likely to suffer smaller decrease in the market value of future projects, and hence their entire market value, compared with those firms with low turnaround probability. This should lead to a negative relation between the post-shock BM and turnaround probability. Our empirical findings support this conjecture by showing that the probability of low BM firms to recover from a negative shock is significantly higher than their high BM counterparts. Importantly, this finding is

[1] Among such portfolios are: negative SUE and high P/E ratio (Dreman and Barry (1995)), past losers and low BM (Daniel and Titman (1999)), financially distressed and low BM (Griffin and Lemmon (2002),, firms with negative accounting results and low BM (Mohanram (2005)), negative profitability and large investments (Chen et al. (2011)), negative gross profits and low BM (Novy-Marx (2011)), and firms for which analysts decrease the short-term growth rate, but not their long-term growth rate (Da and Warachka (2011)).

not driven by heterogeneity in growth opportunities. Our results also suggest the short-term ability to recover from a negative shock is likely to be priced. We find that high turnaround probability stocks experience extremely low returns in the year following the negative shock. Finally, our results show that other portfolios that are in the intersection of high growth and negative attributes, as well as shown to have low realized return, are also characterized by high turnaround probability.

Firm turnaround has been studied extensively in various economic fields. This literature tries to identify the optimal response of the firm to the deterioration in performance, and the factors affecting the probability of success.[2] Among the factors that are found to affect the probability of success are: the type of the negative shock, the response of the company, and the macro-economic conditions. We differ from this literature, as our interest is not in turnaround strategies and the determinates of their success. Instead, we simply assume that heterogeneity in turnaround probability exists across firms. There is no clear definition in the literature for the time frame in which a successful turnaround should occur.[3] Our interest is in the short-term recovery ability of the firm. Accordingly, we measure the firm's performance in the first three years after the initial shock. Arguably, a rational investor will price the probability of a successful turnaround. Hence, changes in the market value of the firm are not a good proxy for successful turnaround, as they measure the success of the firm compared with the initial

[2]Turnaround strategies can be broadly divided into two categories: retrenchment and recovery. In the retrenchment stage, the company improves its cash flows by cutting out expenses, asset reduction, and consolidating operations. The recovery measures are meant to ensure the long-term survivability of the firm. Such strategies include the devoting of new technologies and penetrating new markets (see for example Robbins and Pearce (1992) and Arogyaswamy, Barker and Yasai-Ardekani, (1995)).

[3] Lohrke et al. (2005) noted that the number of different measures for turnaround is probably not much smaller than the number of researchers studying the phenomenon.

expectation of the investors. Instead, we use the accounting performance of the firm to determine the success of the turnaround process.

Analytically, it is straightforward to show that higher turnaround probability (TAP) leads to higher expected future cash flows and hence to higher market value and lower BM. Empirically, our main test examines whether there is a negative relation between post-shock BM and the TAP. We define successful turnaround if two years after the negative shock, the firm has higher earnings than that of the industry median.[4] Estimating a Logit regression, our findings suggest a strong negative relation between the post-shock BM and the proportion of successful turnaround. Low BM firms have roughly 75% higher probability to recover compared with their high BM counterparts.

BM is traditionally associated with growth opportunities. Both short-term recovery and growth lead to higher expected cash flow. Therefore, it is important to distinguish between the two of them. The short-term recovery is largely determined by the correlation between the (low) cash flows at the time of the negative shock and subsequent expected cash flows. Higher (lower) effect of the negative shock on subsequent expected cash flows leads to stronger (weaker) correlation between the current and expected cash flows, and the lower (higher) ability of the firm to recover in the short run. For simplicity, we refer to differences in the short-term ability to recover as differences in the *correlation*. There are two main differences between the effect of *correlation* and growth. First, the *correlation* plays a significant role on expected future cash flows only after a negative shock and has little (if any) effect when the firm performs as expected. In contrast, the effect of growth is largely independent of the firm performance. Second, by definition the effect of the *correlation* on expected cash flows is

[4] The results are robust to various definitions of successful turnaround.

limited to the short term, whereas the effect of growth on expected cash flows is both in the short and long term.

Both higher growth and lower *correlation* lead to lower BM after a negative shock. This suggests that keeping the post-shock BM constant, there should be a positive relation between growth and *correlation.* Firms with relatively high growth and *correlation* are likely to be characterized by small subsequent cash flows that increase at a large pace. In contrast, low growth, low correlation firms should have high subsequent cash flows that increase at a small rate. Because turnaround is measured over the short run, the above leads to the following hypothesis: Controlling for post-shock BM, ceteris paribus, there should be a *negative* relation between growth and TAP.

In order to test this prediction, we need a proxy for growth that is not highly correlated with post-shock BM. As previously noted, our analysis suggests that the BM of negative shock firms is jointly determined by the ability of the firm to recover in the short term and growth opportunities. In contrast, the BM of firms that perform as expected is mainly determined by the growth opportunities. This suggests the BM of the firm before the negative shock (pre-shock BM) should be mainly determined by the growth opportunities of the firm and can be used as a proxy for growth. If our conjectures are correct, then using both pre- and post-shock BM should result in a positive relation between pre-shock BM, turnaround probability and higher (in absolute value) coefficient of post-shock BM. Our empirical findings are consistent with the above. The coefficient of the pre-shock BM is positive and highly significant, whereas the coefficient of current (post-shock) BM almost doubled. Furthermore, limiting the sample for firms with similar growth should lead to stronger relation between BM and TAP. Again, our empirical findings support this prediction.

Next, the relation between turnaround probability and realized future return is examined. While developing a full asset pricing model is outside the scope of this paper, we note that the ability to recover from negative shocks may be priced if these shocks are correlated through time. Our findings show the value spread among negative shock firms is much higher than among other firms. This high spread is driven by the extremely low return of negative shock low BM firms. Importantly, when small firms are censored from the sample (lowest size quintile), the high value spread among negative shock firms continues to be much larger than among non-negative shock firms.

As noted before, this result is consistent with a body of literature that examines the returns of low BM firms with negative attributes. Next, we examine if some of the portfolio that previously reported to have low returns are also characterized by high turnaround probability. Our findings are largely consistent with the above notion. We find higher turnaround probability for the portfolios that are in the intersection of low BM and financial distress (Griffin and Lemmon (2002)), size and financial distress (Garlappi et al. (2008)), past losers and low BM (Daniel and Titman (1999)).

The remainder of the paper is organized as follows: In Section 2, we illustrate the relation between turnaround probability and the BM of the firm after a negative shock. Section 3 presents the data and methodology. Section 4 examines empirically the relation between turnaround probability and BM. Section 5 examines the effect of turnaround probability on returns, and Section 6 concludes the paper.

## 2. A Simple Model

We start our analysis by illustrating the relationship between the probability of a turnaround and BM using a simple setup, which is a variant of the Gordon's constant dividend growth model. We assume that capital markets are perfect and the discount rate is constant r. There are infinite horizon, $t$ = 0, 1,.... . The cash flows of the projects are independently distributed across firms at all times. Each firm faces one-period projects that commence at $t$ = 0, 1.... . All the projects require an investment of I.[5] We assume that dividends are smooth and firms distribute the *expected* cash flows as dividends each period. Hence, the book value is a function of the initial book value and the shock to earnings. We examine the BM of the firm in two periods: zero and one. We assume that in time zero all firms have the same book value and the same expected cash flow in the next period, so that $E_0(F_1) = \mu$.

The cash flow at each period is $F_t = E_{t-1}(F_t) + \epsilon_t,\ t = 1, 2, \ldots$, meaning that $F_1 = \mu + \epsilon_1$. The main difference between our model and the Gordon model is that we assume that the conditional expected cash flows at time one are a function of the initial expectation and the deviation from expectation ($\epsilon_t$) in the previous period, so that:

$$\left(F_{t+j}\right) = (\mu + \theta\epsilon_t)(1 + g)^j \quad . \tag{1}$$

We assume that $\mu > 0$, and similarly to the Gordon model, g is the constant. For the shock $\epsilon_t$, we assume that they have zero mean, i.i.d. across time, and bounded from below at $\underline{\epsilon} < 0$ such that $\frac{(\mu+\theta\underline{\epsilon})(1+g)}{1+r} \geq I$. This later assumption is to make sure that all the projects have non-negative NPV. It also suggests that firms with higher growth rate and lower θ can sustain higher loses and remain operational. Note that the parameter

[5] The assumption of one-period projects is to have investment I each period. Alternatively, one may assume that one long-life project lasts forever, and the initial capital investment does not depreciate.

$\theta > 0$ characterizes the correlation between the cash flows across time. Specifically, the correlation coefficient

$$cor(F_t, F_{t-1}) = \frac{\theta}{1+\theta}. \tag{2}$$

The correlation between cash flows across time (henceforth "correlation") is the measure for the short-term recovery ability of the firm. A lower correlation suggests that the subsequent expected cash flows are less affected by the negative shock. The book value at time zero is $B_0$ and assumed equal across all firms. In time $t$ = 1, the book value is simply the initial book value plus the cash flow from the previous period:

$$B_1 = B_0 + \varepsilon_t. \tag{3}$$

The market value at time $t$ = 0 is the standard value in the Gordon's growth model:

$$M_0 = \frac{Div_0(1+g)}{r-g} = \frac{\mu}{r-g}. \tag{4}$$

So the BM at time $t$ = 0 is:

$$BM_0 = \frac{B_0(r-g)}{\mu}. \tag{5}$$

The market value and the BM value at time zero is only a function of growth rate. Specifically, when growth rate is high, the market value (BM) value is high (low). However, the market value and the BM value at $t$ = 1, 2, ... depends on both the growth rate and the correlation. Specifically:

$$M_1 = \frac{(\mu+\theta\epsilon_t)(1+g)}{r-g} \tag{6}$$

$$BM_1 = \frac{(B_0+\mu+\epsilon_1)\,(r-g)}{(\mu+\theta\epsilon_1)(1+g)}. \tag{7}$$

The effect of growth rate g is similar as before, namely, the market value is monotonically increasing in growth rate, and the BM value is monotonically decreasing in growth rate. However, the effect of the correlation on the market value is dependent on the performance of the firm. When the firm performs as expected ($\epsilon_1 \approx 0$), then the BM of the firm is determined by the growth rate. The higher the absolute value of $\epsilon_1$, the larger the effect of the correlation. For negative shock firms, there is a strong negative relation between the correlation and BM.

To separate the effects of growth rate and correlation, we analyze the relationship between the growth rate, correlation, and turnaround probability (TAP). We define TAP as the probability that the next period cash flow is above some threshold, K: $TAP_t \equiv Prob(F_{t+1} \geq K)$. In period one this probability is:

$$TAP_1 = Prob\big((\mu + \theta\epsilon_1)(1+g) + \epsilon_2 \geq K\big) \tag{8}$$

or:

$$TAP_1 = 1 - N\big(K - (\mu + \theta\epsilon_1)(1+g)\big), \tag{8a}$$

where $N(\cdot)$ is the CDF of $\epsilon$. For negative shock firms, lower correlation and higher growth leads to higher TAP. We can further rewrite the TAP as a function of BM value:

$$TAP_1 = 1 - N\left(K - \frac{I(r-g)}{BM_1}\right). \tag{9}$$

Equation (9) leads to the following empirical predictions: First, for negative shock firms, there is a negative relationship between TAP and the post-shock BM ($BM_1$). Furthermore, controlling for $BM_1$ leads to a negative relation between the growth rate and TAP. Because $BM_0$ is mainly affected by the growth rate, this suggests that controlling for $BM_{1,}$ there should be a positive relation between $TAP_1$ and $BM_0$. Combining the above argument together, the model predicts that $TAP_1$ should be negatively related to $BM_1$ and positively related to $BM_0$.

## 3. Data and Methodology

Our data are obtained from two sources. Monthly data of stock returns and delisting information are drawn from CRSP. Accounting data are retrieved from the COMPUSTAT files. The sample period is July 1976 to June 2010, inclusive. To be included in the sample for calendar year *t*, a firm must have data on CRSP for both June of year *t* and for December of year *t* - 1, as well as COMPUSTAT annual data for both for year *t* and year *t* - 1. We censor from the sample all negative BM firms. The focus of the paper is on the performance and characteristics after a negative shock to current projects. We define a firm as a negative shock firm if it suffered a decrease in profitability that led it to be a low profitability firm. Accordingly, we use two measures to evaluate the performance of the firm. Profitability is calculated as the ratio between net income and total assets (NITA). The change in earnings is the difference in net income between this year and the previous year, scaled by total assets of the previous year:

$$dNI = \frac{NI_t - NI_{t-1}}{TA_{t-1}}.$$

When NI and TA are net income and total assets, respectively.

We use two definitions for negative shock. The wider definition of negative shock firms is those stocks that are in the lowest 30% of both NITA and earnings change (henceforth “negative shock portfolio”). We also use a narrower definition that we labeled as “severe negative shock firms”. These are the firms that are in the lowest quintile of NITA and earnings change. Our sample consists of 125,580 firm years, of which 23,583 (18.8%) are defined as negative shock firms and 15,001 (12.0%) are defined as severe negative shock firms.

There is a large disagreement in the literature regarding the measures of successful turnaround (e.g., Smith and Graves (2005)). Our interest is in the recovery of the firm over a relatively short time span. Therefore, we use a definition that examines the accounting performance of the firm in the subsequent years after the negative shock. Specifically, we define a firm as a successful turnaround if after two years from the negative it has higher profitability (NITA) than the median firm in the industry to which the firm belongs.

## 4. Turnaround Probability and BM

### *4.1. The Effect of Negative Shock on BM*

We start our empirical investigation by examining the effect of negative shock on firm's BM. Fama and French (1993, 1995) argue that low BM firms are characterized by higher growth opportunities. Thus, a decrease in BM is likely to be related to an improvement in the firm's prospect, as explicitly argued by Fama and French (2007). Based on this interpretation, a negative shock is unlikely to lead to a decrease in the BM of the firm. Lakonishok et al. (1994) argue that investors wrongly extrapolate current high earnings into high future expected earnings, leading to mispricing of these stocks. A negative shock to earnings is unlikely to increase this mispricing. Thus, a decrease in BM after a negative shock should not be common. In contrast, both Dichev (1998) and Campbell et al. (2008) findings show that there is a large dispersion in the BM of financially distressed stocks. Campbell et al. (2008) noted that firms are different in the rate they lose market and book value. Yet, they do not suggest any explanations for this result or report how frequently an increase or a decrease in the BM of financially distressed firms can occur. Our model suggests that the BM of the firm following a negative shock is largely affected by the correlation in cash flows across times. Thus, suggesting that negative shock firms are likely to experience a decrease or an increase in negative shock, depending on their turnaround probability.

We start our empirical investigation by examining the effect of negative shock on the firm BM by examining the one-year BM transition matrix from year *t* - 1 to year *t*. This test is similar in nature to the one conducted by Fama and French (2007). Because negative shock stocks are typically small, only firms in the lowest size quintile (NYSE cut-off points) are included in this test.[6] Our focus is on transition from and into the extreme BM portfolios. Thus, for expositional clarity, we collapse quintiles 2–4 into one portfolio that is labeled as medium BM portfolio.

Panel A presents the results for the entire sample of small stocks. The results show that more than three quarters of stocks that are part of medium BM in year *t* – 1 remain in the same portfolio in the preceding year. The proportions of stocks that transit from middle to low and middle to high BM are 7.9% and 16.4%, respectively. Consistent with Fama and French (2007) results, both high and low BM firms tend to converge to medium BM, and the convergence rate is greater for low BM stocks than high BM stocks (40.2% to 27.7%, respectively).

Next, we examine the transition matrix among negative shock firms. Our results show that the migration rate from the medium BM portfolio to the two extreme portfolios increases by almost 50%. Less than two-thirds of the stocks that are defined as medium BM prior to the negative shock remain in this portfolio afterwards. The migration rate to

[6] Note that more than 85% of all negative earnings shock firms are small. Hence, comparing these stocks to all healthy stocks is likely to capture the fact that the BM transition matrix is more stable among large stocks than small stocks. There are no material differences when we limit the sample to the lowest decile.

the lowest BM portfolio almost doubled to 13.7%. In comparison, the migration rate to the highest BM quintile increases by only one-third to 21.9%. We can also report that the migration rate to the low BM portfolio increases with the severity of the shock. For example, when we further limit the sample to stocks that are in the lowest quintile of both NITA and earnings change, the migration rate to the lowest BM portfolio is similar to the migration rate to the highest BM portfolio (18.3% and 18.7%, respectively).

Finally, for comparison reasons, we present in Panel C the transition rate for positive shock firms. We define positive shock firms in a similar fashion to negative shock firms ─ that is firms that are in the top 30% of both NITA and earnings change. Our results show that opposite to negative shock firms, the best performing firms are likely to be medium BM after the positive shock. The migration rate out of the medium BM is less than one-fifth (compared with one-quarter in the overall sample) and the convergence rate is also higher than the overall sample. This is driven by the fact that more than half of high BM firms that experience a positive shock turn into medium BM firms after the shock.

### *4.2. Turnaround Probability and BM*

The next test examines the characteristics and turnaround probability of negative shock firms. Table 2 presents the characteristics of the two measures of negative shock. Negative shock firms are defined as stocks that are in the bottom 30% of both NITA and earnings change, and severe negative shock firms are defined as stocks that are both in the lowest quintile of NITA and the lowest quintile of earnings change. For each of these measures, we present the results for the entire negative shock portfolio and separately for low BM (lowest quintile) firms and high BM (highest quintile).

Row 1 of Table 2 presents the number of stocks in each portfolio. Over the entire sample period there are 23,537 (15,001) negative (severe negative) shock firms. Row 2 shows that, as expected, negative shock firms are typically small. The average size of a negative shock firm is roughly one-quarter of the overall average. Row 3 demonstrates that negative shock firms tend to have extreme values of BM. By construction, the proportion of medium BM firms is 60% of the entire sample. However, it is less than 50% for both measures of negative shock. The negative shock subsample is tilted towards high BM firms (28.1% of all firms), whereas the severe negative shock subsample is tilted towards low BM firms. This is further support to our observation that low BM negative shock firms can sustain higher loses and remain operational. Rows 4–6 examine the accounting performance of negative shock firms. Consistent with previous findings (e.g. Loughran (1997) and Griffin and Lemmon (2002)) results show that among negative portfolio, low BM firms have a much worse accounting performance than high BM firms. This is evident from their lower NITA, worse earnings change as the higher O-score. For example, the average NITA of low BM negative shock firms is -0.46 compared with -0.14 for high BM counterparts.

The last row presents the proportion of firms that were able to successfully turnaround their performance two years after portfolio formation. We define a successful turnaround as those firms that have higher NITA than the median in the same industry (defined according to two SIC numbers) two years after portfolio formation. Our results show that the probability of successful turnaround is similar among the low and high BM portfolios. In each of the measures of negative shock, the difference in turnaround probability between high and low BM is less than 1.5%. On face value, this result is inconsistent with our argument that low BM firms have higher probability of successful turnaround compared with high BM firms. However, as previously documented, the negative shock for low BM firms is much worse than for high BM firms. Taking together the above suggests that for a given shock, the turnaround probability will be higher for low BM firms compared with high BM firms. The two figures below labeled Figure 1A and Figure 1B examine this argument. All negative shock firms are divided into quartiles according to their NITA. Then, we compare the proportion of successful turnaround among low and high BM firms.

Figure 1A
Turnaround probability - all stocks.

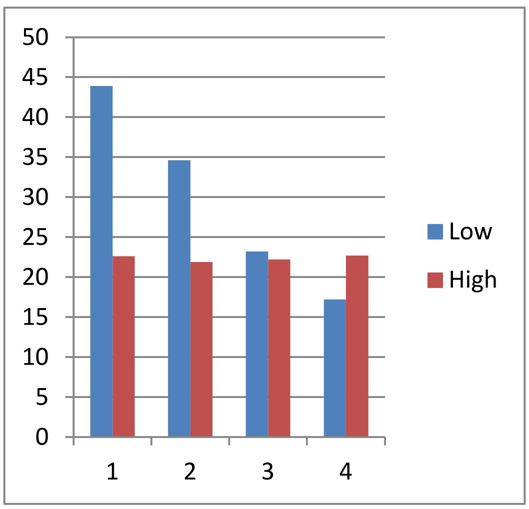
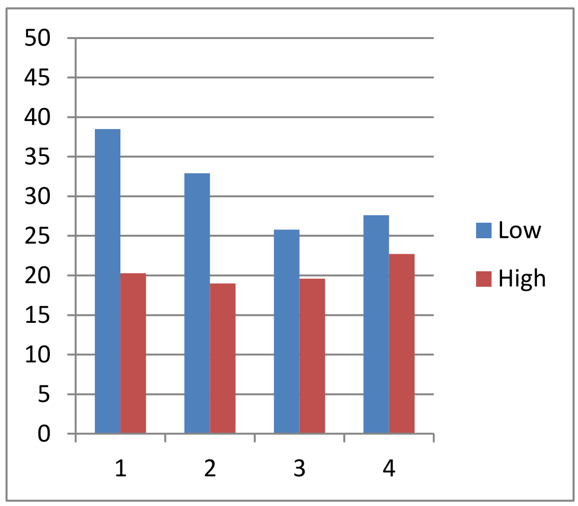



Figure 1B
Turnaround probability - non R&D firms.




The x-axis in the figure is the four NITA quartiles where 4 represents the worst performing stocks. The bars are the proportion of successful turnaround firms.

Figure 1A (left hand side) presents the results for the entire sample. The results show that for stocks that receive relatively low shock (first two quartiles), the probability of successful turnaround is much higher among low BM firms than among high BM firms. For example, among stocks that receive the weakest shock, the proportion of successful turnaround among low BM stocks is almost double than high BM stocks. The two probabilities almost even out in the third quartile. For the worst performing stocks, the relation is opposite with the proportion of successful turnaround firms among high BM firms. It is slightly higher than that of low BM firms (22.6% and 17.6%, respectively).

A possible explanation for the higher turnaround probability of low BM firms among the worst performing stocks is related to research and development (R&D) expenditure. Accounting conservatism requires that R&D will be treated as an expense rather than an investment. Various researchers argue that this treatment leads to downwards bias in both the earnings and the BM value of high intensity R&D firms (e.g. Lev and Sougiannis (1996), Chan et al. 2001)). Another feature of R&D firms is that their projects have higher lifespan than non-R&D firms (Lev and Sougiannis (1996)). Putting the two together suggests that high intensity R&D firms are likely to be the worst performing firms, with low BM and relatively low probability of successful turnaround within two years after portfolio formation. Hence, it may be that the low proportion of successful turnaround of low BM in the worse NITA quartile is related to high consecration of high intensity R&D firms. In order to examine this possibility, we censored from the samples all firms that their ratio of R&D expenditures to total assets higher than the sample medium. Then, we reexamined the turnaround probability of low and high BM firms among the four NITA portfolios. Figure 1B (right hand side) presents these proportions. Our results show that the negative relation between BM to proportion of successful turnaround persists in all NITA portfolios. Thus, our results give the first verification that low BM negative shock firms have higher turnaround probability.

In order to verify the above result, we estimate a Logit regression in which the dependent variable is assigned the value of 1 if the firm has successful turnaround using the same definition as in Table 2. The main independent variable is the BM of the firm. The control variables include R&D expenditures scaled by total assets, size, NITA, earnings change, and years fix-effects. The results of this test are presented in Table 3, Models 1 and 2. Model 1 shows that when BM and R&D expenditures are used as explanatory variables, the coefficient of BM is negative (-0.28) and highly significant. Consistent with the argument that accounting conservatism leads to downwards bias in the earnings of high intensity R&D firms, we find that the coefficient of R&D is negative and highly significant. Adding the rest of the control variables in Model 2 hardly changes the coefficient of BM.

Our analytical analysis suggests that the post-shock BM is determined jointly by the correlation of cash flows across time (θ) and growth. The analysis also suggests that keeping the post-shock BM constant, there should be a *negative* relation between growth and TAP. To illustrate this counter intuitive result, consider two firms with identical post-shock cash flow and market value. If one firm has a higher growth rate than the other, it suggests that this firm has higher long-term cash flows. In order for both firms to have the same market value, it follows that the second firm should have higher short-term cash flows leading to higher turnaround probability.

The empirical challenge is to contract a proxy for growth that is not highly correlated with the post-shock BM. In our model, $BM_0$ plays such a role. Initially, before the result of the first project is known, the BM of the firm is determined solely by the growth rate. But using the first BM is impractical, as it will limit the sample to IPOs.[7] Instead, we use another result of our model: The BM of firms that perform as expected is

[7] The first BM of the firm after the IPO is unlikely to be a measure of $BM_{0,}$ as in most cases; firms exist for a few years before going public.

mainly affected by the growth opportunities. This suggests that if we limit the sample to those firms that perform as expected in the year(s) prior to the negative shock, then the pre-shock BM of the firm can serve as a proxy for growth. In other words, we concentrate on firms that perform according to expectation in the previous year and receive negative shock to earnings in the current year ($\epsilon_{t-1} \cong 0\ and\ \epsilon_t \ll 0$). For these firms, using both the pre- and post-shock BM in the same regression should lead to a negative relation between post-shock BM and TAP and a *positive* relation between the pre-shock BM and TAP. The large transition rate after a negative shock (cf. Table 1) suggests that both measures of BM are unlikely to be highly correlated.

To test the above prediction, we include the lag value of BM as a proxy for growth. In order to ensure that the firm performs as expected prior to the negative shock, we exclude all the firms that receive either a positive or a negative shock in the previous year. In Model 3, we replace the ex-post BM with the ex-ante BM while using the same control variables. Our results show that the coefficient of pre-shock BM is roughly one-quarter of that of post-shock BM. This serves as a first indication that the pre- and post-shock BM are influenced by different economic factors. Model 4 includes both the pre- and post-shock BM. Consistent with our prediction, the coefficient of BM changes sign and becomes positive and highly significant. The coefficient of the post-shock (current) BM is almost double to -0.51. Our analysis suggests that heterogeneity in growth mitigates the relation between post-shock BM and turnaround probability. Hence, selecting firms with similar growth should lead to a stronger relation between the two variables. Accordingly, all stocks that their pre-shock BM is in lowest or highest quintiles are censored from the sample and we re-estimate the same regression as in Model 2.

Consistent with the above analysis, results of Model 5 show that the coefficient of BM increases to -0.55, further supporting our conjunctures.

The positive relation between lag-BM and the proportion of successful turnaround can serve as evidence against many alternative explanations for the relation between BM and TAP. For example, a simpler explanation to ours is that BM is a proxy for growth both before and after the negative shock. Most firms are characterized by the same (low) correlation and the difference in BM is driven by time varying growth rate. Presumably, firms with higher growth are likely to have higher probability for a successful turnaround, leading to the observed relation. However, if BM is a proxy for both pre- and post-shock growth, then the pre-shock BM is redundant in estimating the proportion of successful turnaround. This is inconsistent with our empirical results that show a strong positive relation between the pre-shock BM and the proportion of successful turnaround.

We perform several robustness tests. First, we ensure that our results are not driven by the specifications of our tests. Changing the time period between the negative shock and the next measure that determines if the firm has successful turnaround does not qualitatively change our results. Specifically, we replace the turnaround measure to one and three years after the negative shock and the coefficient of BM remains negative and highly significant. Using the average industry NITA as a benchmark instead of the median NITA, or changing the definition of the industry from two-digit SIC code to one-digit SIC code changes little in our results. Finally, we examine various criteria for censoring stocks from the sample in Models 3–4 and Model 5. Our main results are robust to all of these changes.[8]

*4.3 The Correlation Between Cash Flows*

In our model, the short-term ability to recover is captured by the variable θ ─the correlation between the cash flow after the negative shock and subsequent expected cash flows. The expected cash flows are unobservable, so instead we examine the correlation between the cash flow after a negative shock and subsequent realized cash flows. Griffin and Lemmon (2002) suggest that mispricing is the reason for the underperformance of low BM financially distressed stocks. They argue that for some firms, investors underestimate the correlation between the cash flows from current (failing) projects and future projects. Hence, investors overestimate the value of these firms, leading to both low BM ratio and underperformance. Our argument suggests that heterogeneity in the correlation (θ) leads to differences in BM after a negative shock. We test this prediction by estimating the autocorrelation between the earnings at the time of the negative shock and the average net income in the subsequent three years.[9] If our argument is correct, then among negative shock firms, the earnings persistence of low BM firms should be lower than that of high BM firms. Our approach is consistent with studies by Freeman et al. (1982), Collins and Kothari (1989), and Fama and French (2000). This methodology allows us to measure the correlation between current and future earnings directly at the time that the firm receives the negative shock by estimating the following regression:

$$Ave(NI_{t+1,t+3}) = \alpha + \beta_1 NI_t + \beta_2 Size_t + \beta_2 Size_t + \beta_3 BM_t + \beta_4 NI_t \times BM_t + \beta_5 R\&D_t + DYears + \varepsilon_{t+j}.$$

[8] For example, we define stocks that perform as expected as stocks that are not in the two extreme quintiles of earnings change. In Model 5, we use a respective definition for stocks with the same lag BM, including only firms that are in the middle BM quintile.

[9] Using the net income of one, two, or three years after the negative shock leads to the same qualitatively results.

The important variable is the interaction term between the natural logarithm of BM and net income ($NI_t \times BM_t$). The control variables include BM, size, R&D expenditures, and year fixed effects. The regression is estimated for the entire sample of stocks and separately for negative shock firms.

The first column presents the results for the entire sample. The earnings persistence is higher among low BM stocks, as the coefficient on the interaction variable is negative (-0.12) and significant. The rest of the columns in the table present the result for the negative shock firms only. Column 2 presents the results for the entire negative shock sample. The earnings coefficient on negative shock firms is much lower than that for the entire sample (0.09 compared to 0.72), and the r squared decreases by ten folds. This is consistent with findings reported by Basu (1997) that earnings persistence among losing firms is lower than for profitable firms. Most importantly, we find that the coefficient on the interaction variable changes sign and is *positive* (0.20) and highly significant. Thus, consistent with our analytical derivations, among negative shock firms the earnings coefficient is lower for low BM firms.

Figure 1, Panel B, analyzes the earnings persistence of negative shock firms while excluding high intensity R&D firms. This may give the false impression that our results do not hold for these firms. In Column 3, we include in the sample only those firms with positive R&D expenditures (henceforth the R&D sample). The results show that the coefficient of the interaction variable in the R&D sample is similar to that of the entire portfolio of negative shock firms. This result confirms that among negative shock firms the negative relation between BM and earning persistence exists both for R&D and non-R&D firms.

Finally, we examine whether, controlling for growth, the relation between BM and earnings persistence will increase. As previously noted, the post-shock BM is driven by both growth and correlation (earnings persistence). Hence, controlling for post-shock BM is a noisy proxy for the correlation. This proxy can be improved if we include in the sample only firms with similar growth. Using the lag BM as a control for growth, we limit the sample to firms that are part of the medium BM portfolio in the previous year before the negative shock (similar to Model 5 in the previous table). The results show that the coefficient of the interaction variable almost doubled compared with the results for the entire negative shock sample (0.37 and 0.20, respectively). The r squared of the regression increases from 0.068 for the entire negative shock portfolio to 0.113 when we limit the sample to firms that belong to the medium BM portfolio in the year before portfolio formation.

### 4.4 *Ability to Sustain Negative Shocks*

Next, the relation between post-shock BM and the ability of the firm to sustain loses and remain operational is examined. In our model, we made the simplifying assumption that the earnings are larger then:

$$\frac{(\mu+\theta\underline{\epsilon})(1+g)}{1+r} - I \geq 0. \qquad (10)$$

This is under the condition that the next period project will have a positive NPV. Not surprisingly, it suggests that firms with higher growth and lower *correlation* can sustain higher shock and remain operational. These two factors determine also the post-shock BM. Therefore, a low BM firm should be able to sustain higher loses and remain operational compared with high BM firms. In order to test this prediction, we examine the accounting performances of firms prior to their failure (delisting codes 400–599).

Specifically, we focus on the last recorded NITA and argue that it can serve as a proxy for the highest shock to earnings that the firm received and remain listed. Thus, the following regression is estimated:

$$NITA_t = \gamma_1 Ln(bm)_t + \gamma_2 Ln(Size)_t + \gamma_3 TLTA_t + \gamma_4 R\&D_t + \varepsilon_t,$$

where NITA is the last recorded fiscal year net income to total assets of failing firms, and TLTA is total liabilities to total assets. R&D is the research and development expenditures scaled by total assets, and size is the market value of the firm in June. If our conjectures are correct then the coefficient of BM is expected to be positive.

The results of this test are presented in Table 5, Models 1 and 2. Model 1 uses only size BM as the independent variable. The results show that the coefficient of BM is positive (0.17) and highly significant. This suggests that, as predicted, low BM firms can sustain higher shocks and remain listed. In Model 2, we include R&D expenditures scaled by total assets and the book leverage. The inclusion of R&D expenditures is done in order to ensure that accounting conservatism as previously discussed does not drive our results. Indeed, the coefficient of R&D expenditures is negative and highly significant. The coefficient of BM reduces by roughly one-third to 0.12 but remains highly significant.[10] The overall predictive ability of the model improves materially as the adjusted $R^2$ more than doubled (from 0.18 to 0.30).

In Model 3, we add to the regression equation the lag value of BM. As in previous tests, the inclusion of the lag BM is meant to separate between the effect of growth and the correlation. We expect that the inclusion of lag BM will lead to an increase in

[10] As a robustness test, we change the treatment of R&D expenditures from an expense to an investment with a five-year life span. We find that the coefficient of BM remains positive and significant, whereas the coefficient of R&D reduces by more than half but remains significant. This suggests that R&D intensive firms can sustain larger shocks and remain listed, consistent with the findings of Joos and Plesko (2005).

coefficient of current BM, while the coefficient of lag BM should be negative. Our results support this prediction. The coefficient of BM increases by 0.17, whereas the coefficient of lag BM is negative (-0.08) and highly significant. Finally, in Model 4 we include in the sample only firms that are in the medium BM portfolio in the year before portfolio formation. Again, the result shows a large increase in the coefficient of BM compared with Model 2. Our results support the conjuncture that the correlation plays a key part in the ability of firms to sustain high loses. Our results are also likely to have implications to improvement of bankruptcy models, as they suggest that both current and lag BM should be included as a predictor in order to capture the effect of the correlation.

## 5. Turnaround Probability and Stock Returns

There has been extensive literature that documented negative relation between current BM and future realized returns. Further empirical evidence suggests difference in realized returns between low and high BM (value spread) is especially large among stocks with negative attributes. This later finding is driven by the extremely low return of low BM firms with negative attributes. While developing an asset pricing model is outside the scope of this paper, we suggest that heterogeneity in TAP can serve as an explanation for this finding. A potentially risk-based explanation is that the ability to recover from negative shocks is correlated with the ability to recover from macro-economic shocks. If this is the case, then high TAP firms should present less risk to the investors compared with low TAP firms; and hence their lower return. Alternatively, in a similar fashion to the Griffin and Lemmon (2002) argument, it may be that investors overestimate the probability of successful turnaround, and that this overestimation is concentrated among high TAP. Regardless of the question as to what cognitive bias causes the over pricing of high TAP stocks, the high uncertainty that is associated with negative shock firms is likely to deter arbitrageurs from trying to exploit the mispricing.[11]

We start our examination of the relation between TAP and return by testing whether the value spread is different among negative shock firms and non-negative shock firms. Our core argument is that TAP affects the BM of firms after a negative shock, whereas the BM of non-negative shock is not affected. Therefore, if TAP is correlated with realized returns, then one should expect the value spread to be different between negative shock firms and non-negative shock firms. Table 6, Panel A, examines this question. We estimate Fama McBeth (1973) regressions using three specifications. In the first one, we use the regular size and BM to predict stock returns. Our results are consistent with previous studies by showing negative relation between size and returns and positive relation between BM and returns. The coefficient of BM (-0.33) is similar in magnitude to other studies that use Fama-McBeth regressions (e.g., Loughran (1997) and Fama and French (2008)). Next, we add an interaction variable between negative shock and BM (NegBM). Our results show that as a result of inclusion of the interaction variable, the coefficient of BM reduces to 0.27 but remains statistically significant. Importantly, the coefficient of the interaction variable NegBM is also positive (0.19) and highly significant. This suggests that the BM effect among negative shock firms is much stronger than among non-negative shock firms. In the last row of Panel A, we examine

[11] The distribution of negative shock firms is much more fat tailed than for non-negative shock firms. For example, if arbitrageur decides to short sell a high TAP firm, he/she is facing the risk that the stock will increase sharply. Our untabulated results show that the probability of high TAP firms to be in the top decile of stock return in the next 12 months after portfolio formation is one and a half times larger than non-negative shock firms. Campbell et al. (2008) reports similar findings regarding the returns of financially distressed stocks.

whether the large value spread among negative shock firms is due to low returns of high turnaround (HTAP) firms, high return of low turnaround (LTAP) firms, or both. We do it by replacing the interaction variable NegBM with two dummy variables (HTAP and LTAP), to which we assign the value of one if the firm suffers a negative shock and are part of the low or high BM portfolios. The results show that the larger value spread of negative shock firms is related to the underperformance of low BM negative shock firms, as the coefficient of HTAP stocks is negative (-0.54) and highly significant. In contrast, the coefficient of LTAP firms is small and insignificant.

A potential explanation for our results is that the reason for the higher value spread among negative shock firms is because these stocks are likely to be financially distressed. Arguably, a negative shock is likely to push many of the firms in this portfolio towards financial distress. Indeed, in our sample almost two-thirds (63%) of all negative shock firms are in the highest O-score quintile, and the failure rate (delisting codes 400–599) of negative shock firms is almost three times higher than in the entire sample. Hence, it may be that Panel A results are simply a replication of existing results in the financial distress literature.[12] In order to separate between the two explanations, all small stocks (lowest size quintile NYSE cut-off points) are censored from the sample. This procedure reduces the proportion of stocks in the highest O-score quintile to one-third, and the failure rate reduces and is now lower than the sample average.

We use the same three specifications as in Panel A. The results show that in the first specification the coefficient size becomes insignificant, whereas the coefficient of BM reduces by roughly one-third but remains statistically significant. When we add the

[12] For example, Griffin and Lemmon (2002) and Vassalou and Xing (2004) document higher value spread for financially distressed firms. Griffin and Lemmon (2002) emphasize the extremely low returns of low BM financially distressed stocks.

interaction variable (Row 2), the coefficient of BM further reduces to 0.18, and it is in the borderline of statistical significant. The coefficient of the interaction variable is larger than the coefficient of BM and statistically significant, suggesting that among large stocks the BM effect is more than twice as large among negative shock firms compared with non-negative shock firms. Finally, Row 3 shows that the underperformance is driven by the extremely low return of HTAP stocks. Overall, the results for large firms are as strong as the results for the entire sample even though the negative shock portfolio is much less distressed. This suggests that higher default probability is not the main driving force behind our results.

We note that negative shock firms are mostly small firms. Hence, when small firms are censored, the resulting sample contains a small fraction of negative shock firms. In Panel B, the proportion of negative shock firms out of the entire large stocks sample is only 9.6%. This raises the concern that our results, though statistically significant, relate to a small number of firms. In order to examine this concern, we redefine firms as negative shock if they are in the bottom 30% of NITA and earnings change *among* large firms. The new definition more than doubles the proportion of negative shock to 19.2% among large firms. The proportion of stocks in the highest O-score quintile further reduces to 24%, and the proportion of firms that fail is less than half percent. Thus, the new negative shock portfolio contains twice as much stock, and it is much less distressed than the negative shock portfolio of Panel B. However, the return results hardly change. Importantly, the HTAP portfolio continues to significantly underperform after controlling for size and BM.

Our final test examines whether HTAP probability can explain the low return of other portfolio that are in the intersection of high growth and bad attributes. Specifically, we examine four portfolios: financial distress and low BM (Griffin and Lemmon (2002), past losers and low BM (Daniel and Titman (1999), negative profitability and large investments (Chen et al. (2011), and financial distress and large size (Garlappi et al. (2008)).

We start with the portfolio of financially distressed low BM stocks. Our previous findings show that the low return of HTAP firms is observed, whether the shock is financially distressed or not. Now we ask the opposite question–whether the low returns of low BM financially distressed stocks (Griffin and Lemmon (2002)) can be explained by heterogeneity in turnaround probability. In order to examine this possibility, we divide all stocks to quintiles according to their O-score. Stocks in the highest O-score decile are defined as financially distressed. Then, we examine the probability of successful turnaround among financially distressed stocks using the same definition as throughout the paper. If the low return of low BM financially distressed stocks is related to higher TAP, then the BM coefficient should be negative. We use size, NITA, earnings change, R&D expenditures, and year fixed effects as our control variables.

The results of this test are presented in Panel A of Table 7. In Model 1, we examine the TAP when BM is a sole predictor. Consistent with the TAP explanation, the results show that the coefficient of BM is negative (-0.21) and highly significant. In Model 2, we add to the estimation the R&D expenditures scaled by total assets and year fixed effects. The results show that the coefficient of BM almost doubles in magnitude, whereas the coefficient of R&D is negative and highly significant. This further suggests that accounting conservatism that required R&D expenses to be treated as expenditure and not an investment mitigates the relation between BM and TAP. Finally, Model 3 adds to the regression equation NITA and the change in earnings. The results show that the coefficient of BM hardly changes and remains negative and highly significant. Our findings confirm that the portfolio of low BM financially distressed stocks have HTAP probability. Hence, if TAP can serve as an explanation for the low returns of negative shock low BM stocks, it can also serve as an explanation for the low returns of low BM financially distressed stocks.

Next, we examine the portfolio of financially distressed large firms. Garlappi et al. (2008) argue that deviation from absolutely priority rights can explain the low returns of financially distressed stocks. One of the proxies that they use to examine their hypothesis is the market capitalization of financially distressed firms. They report that the average return of large financially distressed stocks is lower than small financially distressed stocks. We use the same methodology as in Panel A in order to examine the effect of size on TAP among financially distressed stocks. Model 1 uses only size (market value of equity at the end of June) as a sole predictor. Our results show that, as predicted, the coefficient of size is positive and significant. Next, in Model 2, the same control variables as in Panel A are added to the regression. The coefficient of size hardly changes and remains highly significant. The rest of the coefficients enter in the same sign as in Panel A. Finally, we add to the regression the BM of the firm. The inclusion of BM decreases substantially the coefficient of size that becomes statistically insignificant. This finding suggests that both size and BM can serve as a proxy for TAP among financially distressed stocks, and that BM has better explanatory power than size.

Both Asness (1997) and Daniel and Titman (1999) report that the value spread is strongest among past losers, and that momentum is strongest among low BM firms. Both of these findings are derived by the extremely low returns of the low BM past losers portfolio. In Panel C, we examine whether this portfolio is also characterized by high turnaround probability. At the end of each June, all stocks are divided into quintiles according to their average return in the previous six months. Stocks in the lowest quintile are labeled as past losers and are the focus of our tests. If TAP is related to the underperformance of stocks that are both low BM and past losers, then among past losers there should be a negative relation between BM and TAP. Using the same methodology, as the previous two panels, the results confirm our conjecture. Model 1 shows that when using BM as a sole predictor, it is negative and significant. Consistent with previous results, adding R&D expenditure in Model 2 further increases (in absolute value) the coefficients of BM. Adding the rest of the control variables (Model 3) hardly changes the coefficient of BM.

Finally, in Model 4 we examine the portfolio of low profitability and high asset growth. Chen et al. (2011) report that the portfolio that is in the intersection between low profitability and high growth has extremely low average return. We examine whether among low profitability firms, stocks with high asset growth have higher turnaround probability. Unlike other tests in this part, the results are opposite to our conjuncture. Stocks with high asset growth have lower probability of successful turnaround. This result remains regardless of whether asset growth is used as a sole predictor or with the rest of the control variables.

## 6. Conclusion

This paper examines the performance of negative shock firms. Our core argument is that the effect of negative shock on the market value of the firm is largely related to the short-term recovery ability of the firm. Firms with HTAP probability are likely to suffer a relatively small decrease in their market value following a negative shock to earnings and hence are likely to be low BM firms. In contrast, firms with LTAP probability are likely to suffer a large decrease in their market value after a negative shock, suggesting that they are likely to be high BM firms. Our empirical finding supports this argument by showing that negative shock low BM firms have a higher probability of turnaround compared with their high BM counterparts. We conduct two additional tests that support this result. First, we show that the correlation between the (low) cash flow at the time of the negative shock and subsequent cash flows are low among low BM stocks. Second, we show that low BM firms can sustain higher loses and remain operational. Both of these findings are consistent with the idea that negative shock of low BM firms has less affect on subsequent cash flows.

Next, we further seek to refine the definition of stocks that are likely to have high turnaround probability. We note that both high growth and high TAP are likely to lead to low BM after a negative shock. To separate between the two effects, we look at the BM of the firm before the negative shock. We argue that the pre-shock BM is mainly affected by the growth opportunities, whereas the post-shock BM is jointly determined by the TAP and growth. Using the pre-shock BM as a proxy for growth, we show that firms with low pre-shock growth have higher turnaround probability than firms with high pre-shock growth. Again, our two other empirical tests support this conjuncture.

Next, we examine the relation with stock returns. Our findings suggest that the portfolio of negative shock and low BM has extremely low realized return. Importantly, we find that this result is not driven by financial distress. Even when we censor from the sample of all small firms and select negative shock firms only among large stocks, the underperformance of negative shock low BM stocks continues. Finally, we examine whether other portfolio that are in the intersection between high growth and negative attributes are also characterized by low returns. Again, our findings support this hypothesis by showing that the portfolio of past losers and low BM, financially distressed and low BM, and financially distressed and large stocks all has high turnaround probability.

## References


Asness, Clifford S., 1997. The Interaction of Value and Momentum Strategies, *Financial Analyst Journal* 53: 29–36

Arogyaswamy, K., V.L. Barker III, and M. Yasai-Ardekani, 1995. Firm Turnarounds: An Integrative Two-Stage Model, *Journal of Management Studies* 32: 493–525.

Basu, Sudipta, 1997. The Conservatism Principle and the Asymmetric Timeliness of Earnings. *Journal of Accounting and Economics* 24: 3–37.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008. In Search of Distress Risk. *Journal of Finance* 63: 2899–2939.

Chan, L.K., J. Lakonishok, and Theodore Sougiannis, 2001. The Stock Market Valuation of Research and Development Expenditure. *Journal of Finance* 56: 2431–2456.

Chen, Long, Robert Novi-Marx, and Lu Zhang, 2011. An Alternative Three-factor Model, available at SSRN: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1418117

Collins, Daniel W., and S.P. Kothari, 1989. An Analysis of Intertemporal and Cross-sectional Determinants of Earnings Response Coefficients, *Journal of Accounting and Economics* 11: 143–181.

Da, Zhi, and Mitch Warachka, 2011. The Disparity between Long-term and Short-term Forecasted Earnings Growth, *Journal of Financial Economics* 100: 424–442

Daniel, Kent, and Sheridan Titman, 1999. Market Efficiency in an Irrational World. *Financial Analyst Journal*, 55: pp 28–40.

Dichev, Ilia D., 1998. Is the Risk of Bankruptcy a Systematic Risk? *Journal of Finance* 53: 1131–1147.

Dreman, David N., and Michael A. Berry, 1995. Overreaction, Underreaction, and the Low P/E Effect. *Financial Analyst Journal* 51: 21–30.

Fama, Eugene F., and Kenneth R. French, 1992. The Cross-section of Expected Stock Returns. *Journal of Finance* 47: 427–465.

Fama, Eugene F., and Kenneth R. French, 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33: 3–56.

Fama, Eugene F., and Kenneth R. French, 1995. Size and Book-to-Market Factors in Earnings and Returns. *Journal of Finance* 50: 131–155.

Fama, Eugene F., and Kenneth R. French, 2000. Forecasting Earnings and Profitability. *Journal of Business* 73: 161–176.

Fama, Eugene F., and Kenneth R. French, 2007. Migration. *Financial Analysts Journal* 63: 48–58.

Fama, Eugene F., and Kenneth R. French, 2008. Dissecting Anomalies. *Journal of Finance* 63: 1653–1678.

Fama, Eugene F., and J.D. MacBeth, 1973. Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy* 81: 607–636.

Freeman, Robert N., James A. Ohlson, and Stephen H. Penman, 1982. Book Rate-of-Return and Prediction of Earnings Changes: An Empirical Investigation. *Journal of Accounting Research* 20: 639–653.

Garlappi, Lorenzo, Tau Shu, and Hong Yan. (2008), Default Risk, Shareholder Advantage and Stock Returns. *The Review of Financial Studies,* 21: 2743-2778.

Griffin, John M., and Michael L. Lemmon, 2002. Book-to-Market Equity, Distress Risk, and Stock Returns. *Journal of Finance* 57: 2317–2336.

Joos, P, and G. Plesko, 2005. Valuing Loss Firms. *The Accounting Review* 80: 847-870.

Lev, B., and T. Sougiannis, 1996. The Capitalization, Amortization, and Value-relevance of R&D. *Journal of Accounting and Economics* 21: 107–138.

Lakonishok, Josef, Andrei Shleifer and Robert W. Vishny, 1994. Contrarian Investment, Extrapolation, and Risk. *Journal of Finance* 49: 1541-1578.

Lohrke, Franz T., Arthur G. Bedeian, and Timothy B. Palmer, 2004. The Role of Top Management Teams in Formulating and Implementing Turnaround Strategies: A Review and Research Agenda. *International Journal of Management* Reviews 5: 63–90.

Loughran, Tim. 1997. Book-to-Market across Firm Size, Exchange, and Seasonality: Is There an Effect? *Journal of Financial and Quantitative Analysis* 32: 249–268.

Mohanram, Partha S., 2005. Separating Winners from Losers among Low Book-to-Market Stocks Using Financial Statement Analysis. *Review of Accounting Studies* 10: 133–170.

Novy-Marx, R., 2012, The other side of value: The gross profitability premium, university of Rochester Working Paper.

Robbins, D. K. and J. A. Pearce, 1992. 'Turnaround: Retrenchment and Recovery', *Strategic Management Journal* 13: 287–309.

## Table 1: One-Year Transition Matrix of BM

This table presents the one-year transition matrix for the BM of small stocks. At the end of each June of year $t – 1$, all positive BM stocks are allocated into three BM portfolios: Low (lowest BM quintile), Medium (quintiles 2–4), and High (highest quintile). Then, for each stock we examine, its BM in the following June (year $t$). We include in this analysis only stocks that belong to the smallest size quintile (NYSE cut-off points). All stocks that do not have a *positive* BM ratio in both consecutive years are deleted from the sample. Rows in the tables represent the BM at year $t – 1$, whereas the columns represent the BM in the current year (year $t$). The results of this test are reported in Panel A.

In Panel B, we repeat the same procedure while limiting the sample to negative shock firms. We define negative shock firms as a firm that is in the bottom 30% of net income to total assets (NITA) *and* the bottom 30% of earnings change (defined as the difference between this year's net income and the previous year scaled by total assets of the previous year). Finally, in Panel C, we repeat this test for positive shock firms. We define positive shock in a similar way to negative shock–firms that are in the top 30% of both NITA and earnings change.

**Panel A: Transition matrix for all small firms (n = 69,042)**

| | **BM (year *t*)** | | |
|---|---|---|---|
| **BM (year *t* - 1)** | **Low** | **Medium** | **High** |
| Low | 57.1 | 40.2 | 2.7 |
| Medium | 7.9 | 75.7 | 16.4 |
| High | 1.3 | 27.7 | 71.1 |

**Panel B: Transition matrix for negative shock firms (n = 17,323)**

| | **BM (year *t*)** | | |
|---|---|---|---|
| **BM (year *t* - 1)** | **Low** | **Medium** | **High** |
| Low | 63.3 | 33.0 | 3.6 |
| Medium | 13.7 | 64.4 | 21.9 |
| High | 2.5 | 25.1 | 72.4 |

**Panel C: Transition matrix for positive shock firms (n=8,625)**

| | BM (year t) | | |
|---|---|---|---|
| BM (year t-1) | Low | Medium | High |
| Low | 56.8 | 40.7 | 2.4 |
| Medium | 11.2 | 81.4 | 7.4 |
| High | 1.5 | 55.3 | 43.3 |

## Table 2: Characteristics of Negative Shock Firms

This table presents the characteristics of negative shock firms. At the end of each June, we sort all sample stocks into quintiles according to their NITA and change in earnings. We use two different definitions for negative shock. The first defines stocks that are in the lowest 30% of both NITA and earnings changes. The second measure defines stocks that are in the lowest quintile of both NITA and earnings change as severe negative shock firms. Additionally, we sort stocks to three portfolios of BM: Low (lowest quintile), Medium (quintiles 2–4), and High (highest quintile). We present the results for the entire negative shock portfolio (using both definitions) and separately for low and high BM portfolios between the two negative shock portfolios. Row 1 presents the number of firms in each portfolio. The numbers in brackets are the proportion of low and high BM stocks out of the entire portfolio of (severe) negative shock firms. Row 2 presents the average natural logarithm of the market equity of each portfolio as of June year *t*. Row 3 presents the average BM equity. Row 4 presents the average net income to total assets. Row 5 presents the average earnings change as defined in Table 1. Row 6 presents the average O-score. Finally, in Row 7, we present the percentage of successful turnaround firms in each portfolio. We define firms as successful turnaround if their average NITA is higher than the median among stocks with the same industry (the definition of industry is according to two-digit SIC code).

| | | **Negative shock** | | | **Severe negative shock** | | |
|---|---|---|---|---|---|---|---|
| | | **Low BM (HTAP)** | **High BM (LTAP)** | **All** | **Low BM (HTAP)** | **High BM (LTAP)** | **All** |
| (1) | Number of firms | 5,514 (23.4%) | 6,602 (28.1%) | 23,537 | 4,477 (29.6%) | 3,563 (23.8%) | 15,001 |
| (2) | Size | 10.98 | 9.79 | 10.55 | 10.84 | 9.43 | 10.34 |
| (3) | BM | 0.15 | 2.14 | 0.98 | 0.15 | 2.13 | 0.88 |
| (4) | NITA | -0.46 | -0.14 | -0.25 | -0.47 | -0.17 | -0.30 |
| (5) | Earnings change | -0.35 | -0.13 | -0.22 | -0.36 | -0.15 | -0.24 |
| (6) | O-score | 4.33 | 1.24 | 2.26 | 4.88 | 2.00 | 3.18 |
| (7) | % successful turnaround | 23.69 | 22.31 | 26.74 | 21.85 | 22.90 | 23.96 |

## Table 3: BM and Turnaround Probability

This table examines the turnaround probability among negative shock firms. We define negative shock as in previous tables and censor from the sample all non-negative shock firms. Then we estimate the following Logitic regression:

$$Turn_{t+2} = \alpha + \beta_1 BM_t + \beta_2 R\&D_t + \beta_3 Size_t + \beta_4 NITA_t + \beta_5 dNI_t + Dyear + \varepsilon_t.$$

Where $Turn_{t+2}$ is a binary variable to which we assign the value of one if the NITA of the firm two years after portfolio formation (the negative shock) is larger than the median NITA among all the firms that belong to the same industry (defined as two-digits SIC code). BM is the book value of equity divided by the market value of equity as in Fama and French (1992). R&D is the research and development expense scaled by total assets. Size is the market value of equity as of June of year *t*. NITA and dNI are defined in the same way as previous tables. DYears is the matrix that controls for year fixed effects.

Model 1 uses only BM and R&D as explanatory variables. Model 2 includes the rest of the control variables. In Model 3, we replace the BM with the BM of the firm in the previous year (lag BM). Model 4 includes both current and lag BM. Finally, in Model 5, we limit the sample to stocks that are part of the medium BM (quintiles 2–4) in the year prior to the negative shock.

In order to control for outliers in each regression, estimations for the lowest and highest 1% are set equal to 1% and 99%, respectively. A *, **, *** denotes significance at the 10%, 5%, 1%, respectively

| | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** |
|---|---|---|---|---|---|
| BM | -0.250*** (0.023) | -0.284*** (0.026) | | -0.514*** (0.043) | -0.548*** (0.058) |
| R&D | -2.849*** (0.183) | -2.198*** (0.208) | -1.539*** (0.270) | -1.608*** (0.274) | -2.393*** (0.297) |
| Size | | 0.0560*** (0.011) | 0.099*** (0.013) | 0.063*** (0.013) | 0.076*** (0.015) |
| NITA | | 0.579*** (0.010) | 0.941*** (0.164) | 1.285*** (0.175) | 1.230*** (0.179) |
| dNI | | 0.558*** (0.122) | -0.947** (0.222) | -0.937** (0.226) | -1.299*** (0.253) |
| Lag BM | | | -0.072** (0.030) | 0.261*** (0.039) | |
| Years fix effects | No | Yes | Yes | Yes | Yes |
| # of observations | 15,740 | 15,740 | 10,762 | 10,762 | 7,459 |

## Table 4: Earnings Persistence Among Negative Shock Firms

This table presents the earnings persistence of the entire sample and among negative shock firms. We estimate the following linear regression for both the entire sample and its three subsamples:

$$Ave(NI_{t+1,t+3}) = \alpha + \beta_1 NI_t + \beta_2 Size_t + \beta_2 Size_t + \beta_3 BM_t + \beta_4 NI * BM_t + DYears + \varepsilon_{t+j}.$$

Where:
$NI_{t+1}$ is the average net income of the firm in the three years after portfolio formation
$NI_t$ is the net income of the firm at portfolio formation
$Size_t$ is the natural logarithm of the market value of the firm at portfolio formation
$BM_t$ is the natural logarithm of the BM of the firm at portfolio formation
BM*NI - an interaction variable between BM and NI
DYears is the matrix that controls for year fixed effects
The first column presents the results for the regression estimates for the entire sample. Columns 2–4 present the result for negative shock only. Column 2 presents the results for the entire sample of negative shock firms. Column 3 presents the results for negative shock firms with positive R&D expenditures. Finally, the last column presents the results for negative shock firms that are part of the medium BM portfolio in the year before the negative shock.
In order to control for outliers in each regression, estimations for the lowest and highest 1% are set equal to 1% and 99%, respectively. A *, **, *** denotes significance at the 5%, 1%, 0.1%, respectively.

| | **All Sample** | **Negative Shock Only** | | |
|---|---|---|---|---|
| | | **All** | **Positive R&D** | **Lag Med BM** |
| NI | 0.716***<br>(0.003) | 0.093***<br>(0.018) | 0.112***<br>(0.026) | 0.190***<br>(0.0285) |
| BM | 12.15***<br>(0.192) | 8.697***<br>(0.425) | 9.999***<br>(0.644) | 12.45***<br>(0.652) |
| Size | 2.830***<br>(0.375) | 7.018***<br>(0.645) | 6.527***<br>(1.024) | 10.56***<br>(1.470) |
| BM*NI | -0.120***<br>(0.002) | 0.204***<br>(0.013) | 0.231***<br>(0.018) | 0.367***<br>(0.024) |
| R&D | | | -40.37***<br>(6.775) | |
| Years fix effects | Yes | Yes | Yes | Yes |
| # of observations | 98,583 | 17,142 | 9,618 | 7,952 |
| Adj. $R^2$ | 0.718 | 0.068 | 0.084 | 0.113 |

## Table 5: Last Recorded NITA of Failing Firms

In this table, we examine the effect of BM on the ability of firms to receive a negative shock to current projects and yet remain listed. We test this question by examining the last net income to net assets (NITA) of failing firms, prior to their delisting from the exchange. Thus, for all firms that fail between July of year *t* and June of year *t* + 1, we use the previous year's annual data in order to calculate NITA, and we use it as a dependent variable. The main independent variable is the natural log of the BM ratio. Control variables include the value of market equity (size), R&D expenditures scaled by total assets, book leverage defined as the ratio between total liabilities and total assets (TLTA), and year fixed effects. Thus, we estimate the following regression:

$$NITA_t = \alpha + \beta_1 BM_t + \beta_2 Size_t + \beta_4 R\&D_t + \beta_3 TLTA_t + \varepsilon_t,$$

In Model 1, we use only size and BM. In Model 2, we add the R&D to total assets. In Model 3, we add the lag value of BM, whereas Model 4 includes only firms that have been part of the medium BM portfolio in year $t$ - 1.
In order to control for outliers in each regression, estimations for the lowest and highest 1% are set equal to 1% and 99%, respectively. A *, **, *** denotes significance at the 5%, 1%, 0.1%, respectively.

| | **Model 1** | **Model 2** | **Model 3** | **Model 4** |
|---|---|---|---|---|
| BM | 0.168***<br>(0.00851) | 0.115***<br>(0.00844) | 0.170***<br>(0.0122) | 0.162***<br>(0.0150) |
| Size | 0.0784***<br>(0.00818) | 0.0623***<br>(0.00758) | 0.0526***<br>(0.00800) | 0.0605***<br>(0.0101) |
| R&D | | -1.719***<br>(0.087) | -1.781***<br>(0.0943) | -1.283***<br>(0.121) |
| Book leverage | | 0.0484<br>(0.0379) | 0.0785*<br>(0.0422) | 0.172***<br>(0.0559) |
| Lag BM | | | -0.0814***<br>(0.0122) | |
| Years fix effects | Yes | Yes | Yes | Yes |
| # of observations | 2,434 | 2,434 | 2,041 | 913 |
| Adj. R | 0.177 | 0.300 | 0.321 | 0.320 |

$$NITA_t = \alpha + \beta_1 BM_t + \beta_2 Size_t + \beta_4 R\&D_t + \beta_3 TLTA_t + \varepsilon_t$$

**Table 6: Turnaround Probability and Returns**

The table shows the average slopes and standard errors for monthly cross-section regression [Fama-McBeth (1973)] in order to predict stock returns between July$_t$ to June$_{t+1}$. The variables used in order to predict stock returns are:
Size - The natural log of market equity is June$_t$.
BM - The natural log of BM
NegBM- an interaction variable between BM and negative shock
HTAP - is a dummy variable to which we assign the value of one if the firm is in the lowest BM and quintile and defined as negative shock firm
LTAP - is a dummy variable to which we assign the value of one if the firm is in the lowest BM and quintile and defined as negative shock firm
We test the predictive ability of these variables for the entire sample (Panel A). In Panel B, we estimate the regression for after censoring all small firms (lowest size quintile NYSE cut-off points). In Panel C, we redefine negative shock firms as stocks that are in the bottom 30% of NITA and earnings change among large firms. The proportion of firms that are defined as negative shock increases from 9.6% in Panel B to 17.6% in Panel C.
Numbers in brackets are the standard errors. A *, **, *** denotes significance at the 5%, 1%, 0.1%, respectively.

**A. All sample stocks**

| | Size | BM | NegBM | HTAP | LTAP |
|---|---|---|---|---|---|
| **Model 1** | -0.148** | 0.332*** | | | |
| | (0.051) | (0.081) | | | |
| **Model 2** | -0.157** | 0.270*** | 0.188** | | |
| | (0.049) | (0.074) | (0.067) | | |
| **Model 3** | -0.157** | 0.284*** | | -0.508*** | 0.035 |
| | (0.049) | (0.078) | | (0.161) | (0.149) |

**B. Large stocks - negative shock portfolio remains the same**

| | Size | BM | NegBM | HTAP | LTAP |
|---|---|---|---|---|---|
| **Model 1** | -0.056 | 0.223** | | | |
| | (0.050) | (0.097) | | | |
| **Model 2** | -0.065 | 0.180* | 0.231* | | |
| | (0.049) | (0.090) | (0.104) | | |
| **Model 3** | -0.066 | 0.188* | | -0.714** | -0.034 |
| | (0.049) | (0.091) | | (0.244) | (0.248) |

C. **Large stocks - negative shock portfolio redefined**

| | Size | BM | NegBM | HTAP | LTAP |
|---|---|---|---|---|---|
| **Model 1** | -0.056 | 0.223* | | | |
| | (0.050) | (0.097) | | | |
| **Model 2** | -0.065 | 0.175 | 0.197* | | |
| | (0.049) | (0.090) | (0.089) | | |
| **Model 3** | -0.065 | 0.195* | | -0.605** | -0.086 |
| | (0.049) | (0.091) | | (0.206) | (0.141) |

**Table 7: Turnaround Probability and Asset Pricing Anomalies**

In this table, we examine the turnaround probability of four asset pricing return regularities that are reported in previous literature. The four anomalies are: the low return of financially distressed low BM firms (Panel A), the low returns of financially distressed large stocks (Panel B), the low returns of past losers low BM firms (Panel C), and low profitability high investment portfolio (Panel D). All these anomalies are in the intersection between low attributes and high growth. In each of the tests, we limit the sample according to the negative attributes (i.e., financial distress, low profitability, and past losers). We define a firm as a successful turnaround stock in the same manner as Fig. 1 (higher NITA than the industry average two years after it was defined as a negative attribute firm). Finally, we examine whether stocks that are part of the underperforming portfolio have a higher turnaround probability by estimating a Logit regression.

*Panel A: Financially distressed low BM stocks*

At the end of each calendar year, all stocks are being sorted according to their O-score. Stocks in the highest (most distress) quintile of O-score are defined as financially distressed. We censor from the sample all non-distressed stocks and examine the turnaround probability of financially distressed firms. The main explanatory variable is the BM of the firm, whereas the control variables include R&D expenditure scaled by total assets, NITA, earnings change (dNI) and years fix effects.

*Panel B: Financially distressed large stocks*

Stocks are defined as financially distressed in the same manner as Panel A. The main explanatory variable is the size (market value of equity) of the firm. Control variables are the same as in Panel A plus BM.

*Panel C: Past losers and low BM*

At the end of each June, all stocks are sorted according to their average returns in the previous six months. Stocks in the lowest quintile are defined as past losers. Then, we censor all stocks that are not part of the past losers portfolio.

*Panel D: High investment and low profitability*

At the end of each June, we divide all stocks according to their NITA. We define all stocks in the lowest NITA quintile as low profitability and censor other stocks from the sample. The main explanatory variable is the asset growth (defined as percentage change in total assets between year$_t$ and year$_{t+1}$).

**Panel A: Financially distressed low BM stocks**

| | BM | R&D | NITA | dNI | Year Fix effects |
|---|---|---|---|---|---|
| **Model 1** | -0.218*** | | | | No |
| | (0.020) | | | | |
| **Model 2** | -0.395*** | -3.885*** | | | Yes |
| | (0.023) | (0.172) | | | |
| **Model 3** | -0.373*** | -2.381*** | 1.124*** | 0.333*** | Yes |
| | (0.025) | (0.214) | (0.095) | (0.081) | |

**Panel B: Financially distressed large stocks**

| | Size | R&D | NITA | dNI | BM | Year Fix effects |
|---|---|---|---|---|---|---|
| **Model 1** | 0.128*** | | | | | No |
| | (0.010) | | | | | |
| **Model 2** | 0.130*** | -1.996*** | 1.009*** | 0.382*** | | Yes |
| | (0.010) | (0.210) | (0.095) | (0.104) | | |
| **Model 3** | 0.017 | -2.405*** | 1.093*** | 0.341*** | -0.363*** | Yes |
| | (0.011) | (0.210) | (0.096) | (0.086) | (0.025) | |

**Panel C: Past losers and low BM**

| | BM | Size | R&D | NITA | dNI | Year Fix effects |
|---|---|---|---|---|---|---|
| **Model 1** | -0.672*** | | | | | No |
| | (0.033) | | | | | |
| **Model 2** | -0.826 | 0.184*** | -3.616*** | | | Yes |
| | (0.040) | (0.097) | (0.247) | | | |
| **Model 3** | -0.789 | 0.128*** | -1.083*** | 3.533*** | -0.598*** | Yes |
| | (0.041) | (0.010) | (0.291) | (0.185) | (0.145) | |

**Panel D: High investment and low profitability**

| | AG | BM | Size | R&D | NITA | Year Fix effects |
|---|---|---|---|---|---|---|
| **Model 1** | -0.194*** | | | | | No |
| | (0.019) | | | | | |
| **Model 2** | -0.216*** | -0.166*** | 0.050*** | | | Yes |
| | (0.020) | (0.025) | (0.013) | | | |
| **Model 3** | -0.249*** | -0.294*** | 0.047*** | -2.394*** | 0.599*** | Yes |
| | (0.022) | (0.027) | (0.013) | (0.192) | (0.086) | |