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Does Financial Distress Risk Drive the Momentum Anomaly? -Evidence from the U.S. Market

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Abstract
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PURPOSE OF THE STUDY

The main objective of this thesis is to test whether the momentum effect is driven by financial distress risk, a new theory which has been recently proposed by Agarwal and Taffler (2008) in their UK-based study, using data collected from U.S. manufacturing industry. Furthermore, this thesis also investigates the existence of a link between distress risk and other two market anomalies, i.e. size effect and value effect, which has been suggested but not fully agreed in previous papers. Altman's (1968) z-score bankruptcy prediction model is specifically chosen to determine sample firm's financial health status, and all the tests in this study are conducted on this basis.

DATA

The data set used in this thesis consists of all American manufacturing firms listed on NYSE, AMEX and NASDAQ with assets over $ 1 million. All accounting data and stock market data are retrieved from Thomson ONE Bank database. Other market index data (market return, one-month T-bill rate, return on size factor and book-to-market factor) is retrieved from Professor Kenneth R. French's website. 20-year period is covered in this study starting from June 1989 through June 2009.

RESULTS

The sample-based evidence obtained in this paper is found inconsistent with Agarwal and Taffler's (2008) argument. More specifically, although the market underreaction to financial distress risk is proved and the momentum effect phenomenon is found, my results do not show that the momentum effect vanishes after financial distress risk factor gets controlled – the momentum effect is not proxying for financial distress risk. On this basis, I have to conclude that Agarwal and Taffler's (2008) new theory regarding the relationship between momentum effect and distress risk is not applicable on the U.S. market. In addition, I found no evidence to suggest firm size and book-to-market equity are capturing distress risk.

KEYWORDS

Altman's z-score, distress risk, market underreaction, momentum effect

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1. Background and Motivation

Financial distress is a term used in general to indicate a condition when promises of a business entity to creditors are broken or honored with difficulty.[1] Sometimes this problem might be just temporary to a firm, but if the financial status of the firm cannot be improved, then financial distress will eventually lead the questioned firm to bankruptcy. Financial distress is costly to the firm's creditors, and so is to its equity holders, because whenever a firm falls into financial distress, there is a potential risk of losing all the capital that shareholders of that firm have to face. Even though, theoretically speaking, a bankrupt firm's shareholders are eligible to receive a payback from the liquidation of the firm after all the credits have been paid off, in most of the bankruptcy cases the money from the liquidation may only be able to barely cover its credits. Even if there is anything left for shareholders, the amount would be just almost meaningless comparing to the original amount of money invested in the firm.

The foreseeable great deal of capital loose as a result of a firm's bankruptcy that shareholders are going to face automatically puts equity investors on the alert for any information in the market which signals the potentiality of a firm going bankruptcy. As the road leading a firm to a bankruptcy always unexceptionally begins with a financial distress status, how the market would actually react to financial distress risk has, as a result, caught quite noticeable amount of attentions from the academic word. This topic has attracted even more attention in the past two decades possibly due to the fact that the rate of insolvency and business failure has dramatically increased since about 1980 (Altman, 1993; Dichev, 1998), yet a consensus has not been reached. While the scholars on one side stand on a market underreaction story (Dichev, 1998; Lamont, Polk, and Saa-Requejo, 2001, Griffin and Lemmon, 2002; Ferguson and Shockley, 2003; Campbell, Hilscher, and Szilagyi, 2006), the scholars on another side base their argument on the efficient market theory, and they believe that distress risk is systematic risk which can be proxied by size and book-to-market factor, and therefore market will adjust the security return to a higher level to correspond with the higher embedded risk in the financially distressed firm (Chan and

[1] Under the broad meaning of the term "financial distress risk", more exact definitions can be further elaborated for other commonly used terms, such as "credit risk", "counterparty risk (default risk)", "insolvency risk" and " bankruptcy risk" etc. as discussed in Altman (1993), but all these terms are used loosely and interchangeably for the purpose of this study.

Chen, 1991; Fama and French, 1992; Vassalou and Xing, 2004;). As the "old" debate continues, new exploration in this field has moved the focus of the topic one step further. After realizing that the market underreaction story of Dichev (1998) among others was confirmed as well in the UK market, Agarwal and Taffler (2008), based on the sample of their study, proposed a new explanation for momentum effect, which is related to the market underreaction to financial distress risk. According to them, it is eventually financial distress risk that drives the momentum anomaly.

The first aim of this study is to continue the previous studies on investigating if financial distress risk is the hidden risk factor shared by small-sized firms and firms with high book-to-market equity have. In other words, whether distress risk is the fundamental explanation for the higher stock returns on those firms. Although Dichev (1998), Cambell, Hilscher, and Szilagyi (2006) among others have already provided empirical evidence which they found hard to reconcile with this assumed relationship, as the different period is considered and different methodologies are applied, this study further contributes to this area by offering additional insight into the relationship between financial distress risk and size effect or between financial distress risk and book-to-market effect (value effect). The investigation of the two relationships of interest is conducted on both univariate-analytical and multivariate-analytical level. The results are found inconsistent with distress factor hypothesis of Chan and Chen (1991) and Fama and rench (1992), who claimed that distress risk is the driving force behind size and value effect. More specifically, it is found that, after controlling size and book-to-market factor, financially distressed firms do not outperform over financially healthy firms.

Secondly, as the main focus of this study, the relationship between momentum effect and financial distress risk is examined in depth. Even though based on UK data Agarwal and Taffler (2008) have concluded financial distress risk as the driving force of the momentum anomaly in their study, it is necessary to have it more widely tested in order to see if that finding can speak for the market situation in general. For this reason, my study is contributed to fill part of the gap by conducting a similar kind of study on the U.S. market. Besides that a similar univariate analysis applied in studying the relation between financial distress risk and size/value effect is carried out to investigate the link that momentum effect has with financial distress risk, this study also employs the Fama and MachBeth's (1973) cross-sectional regression methodology to examine that relation on a multivariate level. Contrary to the findings reported in Agarwal and Taffler's (2008) paper, the empirical evidence obtained in this study are found not in line with their argument on the link between financial distress risk and momentum effect. In the series of univariate analyses, no evidence of market underreaction to distress risk is found, nor do distressed stock returns show a continuous pattern as expected under Agarwal and Taffler's (2008) claimed cause-consequence relationship between distress risk and momentum effect. Nevertheless, in the cross-sectional regression analysis, the previously claimed negative relationship between distress risk and stock return (Diche, 1998; Campbell, Hilscher and Szilagyi, 2006) is firmly proved, and momentum effect is also shown to exist among the collected samples. However, unlike the results obtained in Agarwal and Taffler's (2008) study where the same methodology was applied, momentum effect does not vanish away after financial distress risk factor is added to the regression model. In fact, the significance of the estimated coefficients of the momentum variable and the distress risk variable, respectively, is most enhanced when both variables are included in the regression model. Therefore, based on the sample of this study, no evidence shows that momentum effect is driven by financial distress risk, same conclusion as Agarwal and Taffler's (2008) on the linkage between momentum effect and financial distress risk can not be reached in U.S. market.

The remainder of the study is organized as follows. Section 2 briefly introduces the main empirical findings in the field; Section 3 provides two sets of hypotheses to be tested in this study; 4 describes the data and sample selection; Section 5 introduces methodologies applied; Section 6 presents the results; and Section 7 draws summary.

2. Prior Empirical Research

The continuous academic interest in the financial distress risk is attributed to its un-neglectable impact on the multiple market players in the real business world. With a consensus on its importance, the main debate on financial distress risk aroused from previous studies, however, has been centralized on the question: whether financial distress risk is systematic risk that can be proxied by size and book-to-market factors?

2.1 Evidence of Distress Risk being a Source of Systematic Risk

Systematic risk, by definition, is risk factor common to the whole economy, therefore is undiversifiable. Given that the market is risk-neutral, if financial distress risk is systematic risk, then any stock in which there is embedded financial distress risk should be given higher risk premium. Recalling that the reason why size and book-to-market factor are included in the Fama and French (1993) three-factor model in addition to the market risk factor is because of the observations that historical-average returns on stocks of small firms and on stocks with high book-to-market ratios are higher than predicted using Capital Asset Pricing model (CAPM) (William Sharpe, 1964; John Lintner, 1965a, b; Jan Mossin, 1966). The observations suggest that size or the book-to-market ratio may be proxies for exposures for sources of systematic risk not captured by the CAPM beta and thus result in higher return premiums which are associated with these factors. The group of researchers who adhere their opinion on financial distress risk being systematic risk believe that both size and value effects are closely linked to financial distress risk, hence, it is the distress risk factor that size factor and book-to-market factor proxy for in the Fama and French (1993) three-factor model. Therefore, based on this belief, although financial distress risk factor is not directly involved in the well known asset pricing model as a variable, it does play a role in asset pricing through its proxies. The belief on the link between distress risk and size/value effect is supported by some empirical evidence reported in the previous research.

In a study of size effect conducted by Chan and Chen (1991), they found that a small firm portfolio normally contains a large proportion on marginal firms, and therefore, the return behavior of marginal firms was examined in particular.[2] By mimicking marginal firms with two size-matched return indices constructed on a basis of dividend changes and leverage respectively, the authors of the study discovered that it is the marginal firm characteristics (low production efficiency, high likelihood of running into a financially distressed situation) but not size that explain the difference in return behavior of large and small stocks. As being at distress risk is one of the two marginal firm characteristics, the relation between distress risk and size effect is therefore suggested based on their findings.

[2] Firms with low production efficiency and high financial leverage

Not only firm size is postulated to be a distress risk capturer, the cross-sectional variation in average returns that is related to distress risk could be captured by book-to-market factor as pointed out by Fama and French (1992). According to them, it is possible that the risk captured by book-to-market factor is the same distress risk factor that causes the size effect (Chan and Chen, 1991), because firms that are judged with poor prospects by the market seem to have low stock prices, and therefore high book-to-market ratio. On the other hand, however, Fama and French (1992) can not eliminate the possibility that the variation in average stock returns associated with the book-to-market factor is just due to market's overreaction to the relative prospects of firms.

Last but not least, Vassalon and Xing (2004) also confirmed that default risk is strongly linked with both size and book-to-market factor by applying Metron's (1974) option pricing model. As documented in their paper, high default stocks earn significantly higher returns than low default stocks, but only if they are small in size or with high book-to-market equity. As a part of the research, the characteristic of default risk is examined through asset pricing test. According to them, default risk is indeed systematic risk. Nevertheless, their results show that, in spite of the fact that SMB and HML contain some default-related information, the better ability of Fama and French (1993) three-factor model in explaining the cross-section of equity returns is not mainly attributed to that the model has captured default risk factor with SMB and HML.

In summary, it seems that the belief that the risk premium given to small-sized firms and firms with high book-to-market equity is attributed to the distress risk born by those firms is not held without any empirical evidence. Thus, despite that if firm size and book-to-market factors are truly good proxies for distress risk, if distress risk is indeed systematic risk, any asset's exposure to this risk source should be, at least to some extent, captured by these two firm factors in an asset pricing model, and eventually reflected in its degree of stock return.

2.2 Evidence against Distress Risk Being a Source of Systematic Risk

As already illustrated earlier, financially distress firms should be given higher risk premium, if distress risk is systematic. In other words, one would expect to find that risk be positively associated with subsequent realized return. However, as it is, findings documented in several literatures are not in line with this expectation. Beaver (1968) is one of the first who document an underperforming phenomenon among financially unhealthy firms. Specifically, he demonstrates that subsequently bankrupt firms underperform the market for up to four years prior to bankruptcy; and the phenomenon is the most obvious during the last year. The finding of lower return earned by distressed firm is also reported in Griffin and Lemmon's (2002) and Ferguson and Shockley's (2003) paper. On the other hand, no significant relation between default probability and equity return is found by Garlappi, Shu, and Yan's (2006) study, where the related expected default frequency (EDF) measure of Moody's KMV is used as an indicator of default probability.

In order to answer the question whether risk of bankruptcy is systematic risk, Dichev (1998) conducted a study on U.S. market. Based on the results obtained, he documented that his finding is hard to reconcile with the risk-return relationship implied by the systematic risk. Specifically, using two bankruptcy prediction models (Altman, 1968; Ohlson, 1980) to indicate distress risk level, Dichev (1998) found that firms with a high probability of bankruptcy are not rewarded with higher returns. Instead, over the period from 1980 to 1995, financially distressed firms underpermed score-determined healthy firms by 1.2% per month on average, as reported in the paper. In a further investigation on the reason for distressed firms' underperformance, Dichev (1998) eliminated the simply assumed risk-return relationship explanation given under perfect market circumstances but concluded that the underperformance of distressed firms is due to market underreaction to distress risk. Besides the main finding, Dichev (1998) also reported some interesting result which showed inconsistency with the assumption of a monotonically positive correlation between bankruptcy risk and book-to-market factor. While low book-to-market ratio is observed in low bankruptcy risk portfolio, he surprisingly found that the book-to-market ratio of the highest bankruptcy risk portfolio is lower than that of the two following portfolios which have relatively lower bankruptcy risk (the inverted U-shape). The explanation given by Dichev (1998) to the inverted U-shaped relation observed between bankruptcy risk and book-to-market factor is that, since the book value of the most distressed firms is often completely wiped out by loses or is even negative, the book-to-market ratio calculated based on those extremely small or negative figure would become an inappropriate indicator of level of bankruptcy risk of a firm.

Therefore, based on this reasoning, the distress explanation for the value effect as suggested by Fama and French (1992) was automatically brought into question.

The underreaction story is also supported by another recent study conducted by Cambell, Hilscher, and Szilagyi (2006). According to them, stocks with high risk of failure tend to deliver anomalously lower average return. Besides that, they also find much higher standard deviations, market betas, and loadings on Fama and French's (1993) size and book-to-market risk factors are associated with distressed portfolios. Therefore, based on the findings, they could not agree with the conjecture that the size and value effects are compensation for the risk of financial distress.

Overall speaking, the doubt about the way of thinking distress risk as systematic risk has been inevitably raised with the consistently observed lower returns on distressed stocks. Moreover, even though both size and value effect are argued by the people holding that same thought to be closely related to distress risk, and therefore generally used as evidence to defense the argument on distress risk being systematic, the findings from recent studies have shown that the conjectured link between either size effect and distress risk or between value effect and distress cannot get fully supported by empirical evidence.

2.3 The Basis for Arguing Distress Risk being Firm-Specific Risk

So, could it be that financial distress risk is firm-specific risk rather than systematic risk after all? We all know that although in a long-term the dynamic change of the rate of return of a security should be always around its expected rate of return, which is determined by its sensitivity to systematic risk, it is very unlikely to find that any actual return on a security turns out to be exactly the same as its expected return rate. The derivation of the actual rate of return on a security from its expected rate of return is a joint result of the unique risk (firm-specific risk) of the issuer of that security, and market reaction to that risk. A market's underracting and overreacting phenomenon have already been long ago realized by market players. With a reasonable understanding that in reality the market is far from perfect, these phenomenon nowadays are also well accepted as one of the inevitable components forming the security market.

There are quite noticable amount of research devoted to examine the market's underreacting and overreacting phenomenon, and also many discussions are held to discuss about the actual factors which trigger these phenomenon.[3] A trading strategy was designed and tested by Jegadeesh and Titman (1993) using U.S. data based on the belief that past winners will continue to beat the market in a subsequent period of time while past losers will continue to be beaten. By buying past winners with capital obtained from selling past losers, the momentum-effect-based strategy was proved to be profitable. However, according to the authors, the profitability of the trading strategies cannot be attributed to lead-lag effects that result from delayed stock price reactions to common factors but firm specific information. Furthermore, as the authors specifically pointed out, the market underreaction to information about the short-term prospects of firms should be the essential factor that causes of the profitability of the trading strategy. In a later study conducted by the same authors but using a different set of data, the momentum-effect-based trading strategy is still proved to be profitable (Jegadeesh and Titman, 2001).

Hong, Lim and Stein (2000) believe that information asymmetry[4] could result inaccuracy in market pricing for a period of time. They tested this hypothesis with the gradual-information-diffusion model (Hong and Stein, 1999) to investigate if stronger momentum effect could be found in stocks for which information gets out more slowly. Based on the results reported in the study, the market pricing is indeed affected by the level of information spreading speed, which is related to firm size and analyst coverage rate. It seems that, firm-specific information, especially negative information, tends to diffuse gradually across the investing public. Therefore, Hong, Lim and Stein's (2000) findings also has an implication of a relationship between market underraction and momentum effect. That is, the market underreaction to firm-specific information might be responsible for the widely observed medium-term continuation of stock returns.

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[3] For the purpose of this study, only literatures on examining market underreaction phenomenon are reviewed in details.

[4] Information asymmetry describes a situation in which one party in a transaction has more or superior information compared to another. This often happens in transactions where the seller knows more than the buyer, although the reverse can happen as well. Potentially, information asymmetry could have impacts on market players' decision making with regard to investment choice. The market price of a security, therefore, could be affected at an aggregate level.

Market underraction has also been given explanations from behavioral finance aspects, the holders of which believe that psychological factors of human beings always have impacts on a decision-making process, therefore result an investment decision to be not as rational as presumed. [5] Daniel and Titman (1999) concluded market underreaction phenomenon as an aggregated effect of investors' overconfidence on their superior knowledge about the firms they choose to invest. On the other hand, without any emphasis on a particular psychological factor, also showed that market underraction might be due to investors' irrational investment decision making. By running a complicated simulation test using their investor's sentiment model, they found that investors tend to be slow in updating their beliefs in response to new public information, which therefore leads to market underreaction. Additionally, this market underreaction, according to them, is believed to generate positive autocorrelation in stock returns.

Even though the explanation for market underreaction phenomenon suggested by Daniel and Titman (1999) or Barberis, Shleifer, and Vishny (1998) is established from a different basis as what Hong, Lim and Stein's (2000) argument is based on, the authors of the three studies at least have reached the same conclusion that market underreaction is the driving force of the momentum effect in stock returns. Furthermore, despite that whether it is information asymmetry, psychological factor or the combination of the two causing the market underreaction phenomenon, the market seems to particularly underreact to firm-specific bad news in the market. Among others, this conclusion is also supported by Lesmond, Schill and Zhou (2004), who pointed out that the majority of relative strength returns (momentum profits) can be attributed to the returns continuation of poor performers.

While poor market performance can be signaled from many different aspects, given the way how the financial distress risk is defined, a high likelihood of a firm going to bankruptcy certainly is one of the most straightforward determinants of a poor market performer. Based on the empirical evidence from previous studies showing that market underreacts to firm-specific risk and the

[5] Struggling in giving plausible explanations for some constantly observe market anomaly using traditional financial theories, behavioral financialists have turned to think that taking psychological factors into account when analyzing the market behavior might be the only way out. In general, behavioral financialists and economists believe that social, cognitive and emotional factors actually play an important role in an economic decision-making process of consumers, borrowers and investors. Consequently, market prices, returns and the allocation of resources will also be affected.

momentum effect is related to market underreaction, if financial distress risk is indeed firm-specific risk, does it mean that financial distress risk is part of the source from which the momentum effect is stemmed? Furthermore, as a firm's financial distress status is an aggregate effect of that firm's continuous poor performances, an even bolder thought would be that could financial distress risk actually be the driving force behind momentum effect?

Following this thought, Avramov, Chordia, Jostova, and Philipov (2007a) devoted effort to explore the relation between momentum and credit risk by examining the stock market performance of credit-rated firms in particular. The credit rates of the sample firms in their study are given by S&P. Same as the standards used by other credit rating agencies, in S&P's credit rating system the lower credit rate a firm has indicates that more serious default (distress) risk problem that firm is in.[6] Therefore, Avramov, Chordia, Jostova, and Philipov's (2007a) study is also one among few, which investigates the relation between momentum and financial distress risk. The authors documented that, momentum payoffs exist among large-capitalization firms that are low rated, but are absent in highly rated small-capitalization firms. Thus, contrast with the conclusion made in other literatures that momentum payoffs are closely associated with information uncertainty variables[7](e.g., Jiang, Lee and Zhang, 2005; Zhang, 2006), their findings suggest the significant credit rating effect on momentum is independent from the effect of all information uncertainty variables. More importantly, as the authors also emphasized in the study that, the momentum strategy profit is mainly contributed by the continuation of low returns for losers with low credit rating, Avramov et al.'s (2007a) findings does shed light on the presumed link between momentum effect and default risk. However, a couple of drawbacks from their research should not be left undiscussed. One of the drawbacks is, since there are only less than 30% of all firms being rated, the applicability of the authors' result is very restricted to a small range. Another drawback is, since the authors did not go deeper into any formal cross-sectional regression analysis, whether the conclusion drawn on the relation between default risk and

[6] However, it is worth noting that Avramov et al. (2007a) noted in the study that, credit risk is not equivalent to financial distress risk. Assuming this conclusion is not given based on some mistaken result, the comment would extend the research topic even further for the future study: if credit risk and financial distress risk are not exactly equivalent to each other as being said, what makes one distinguish from another? If momentum effect is linked with both, what is then the relationship between these two risks?

[7] Information uncertainty is commonly proxied by firm size, firm age, return, volatility, cash flow volatility, and analyst forecast dispersion.

momentum effect is also supported by some formal cross-sectional tests result is left unknown in that study.

Compared with Avramov et al.'s (2007a), Agarwal and Taffler's (2008) approach to investigate the suspected relationship between financial distress risk and momentum effect is more straightforward. By taking the well-known accounting ratio-based bankruptcy prediction model, Z-score model, as the basis to distinguish financially distressed firms and healthy firms, Agarwal and Taffler (2008) found that distressed firms actually underperform their equivalent non-distressed firms after controlling for size and book-to-market factors.[8] This finding, therefore, is consistent with the market underreaction story proposed by Dichev (1998) and Cambell, Hilscher, and Szilagyi (2006) among others, but at the same time implicitly suggested that financial distress risk is not systematic risk. Agarwal and Taffler's (2008) also found the moment effect exist among their sample firms when the firms are sorted into portfolios based on their prior-year returns and their financial health status. It was shown that, averagely speaking, stocks in the distressed firms have lower average monthly prior-year return, and continue to underperform the healthy firm stocks over the subsequent year; and the underperformance showed to be the strongest in the "Loser" group, which was formed by stocks with characteristics suggesting that they are the most difficult to be valued by the market. On the other hand, the authors found that the momentum effect was only statistically significant in distressed group but absent from the nondistressed group, after controlling for the distress risk factor. Based on these findings, a further Fama and MacBeth (1973) cross-sectional regressions analysis was conducted to examine the relation between momentum and distress risk on a 24 four-way-sorted portfolios basis and on a multivariate level. Besides that the market underreaction to distress risk was confirmed again by the negative estimate coefficient obtained for the distress risk factor, the main finding from the cross-sectional regression analysis was that the momentum factor appeared to be significantly positively correlated with portfolio's average monthly return over the subsequent year in the absence of distress risk factor, but once the distress risk factor was added to the regression model,

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[8] Since Agarwal and Taffler's (2008) study is based on UK market, UK-based Z-score bankruptcy model (Taffler, 1983, 1984; Agarwal and Taffler, 2007) is employed: $z = 3.20 + 12.18x_1 - 2.50x_2 - 10.68x_3 + 0.029x_4$ The main difference between this model and Altman's Z-score model is, instead of taking Z-score of 1.81 as the cutting point (Altman, 1968), a firm with Z-score smaller than zero is determined to be at risk of bankruptcy in the UK-based Z-score bankruptcy model. However, the model is derived in a similar way to Altman (1968) using a discriminant modeling approach. The UK-based Z-score model

the magnitude of momentum effect was largely reduced, and more importantly, the effect also became statistically insignificant. Furthermore, the link between distress risk and momentum effect was even more explicitly indicated through the introduction of an interaction dummy between momentum and Z-score into the regression model. The regression results showed that while the estimated coefficient of momentum factor stayed statistically insignificant, the estimated coefficient of the interaction dummy was significantly positive at the 0.05 level, suggesting that the observed momentum effect is indeed only associated with distress risk factor. In summary, the findings from Agarwal and Taffler's (2008) suggest a tight link between distress risk and momentum effect. Therefore the study has provided a potential distress factor explanation for the momentum anomaly. Moreover, the finding of the study is also a confirmation of the market underreaction story argued by Beaver (1968), Dichev (1993), and Cambell, Hilscher, and Szilagyi (2006). Based on the findings, it seems that the market is unable to appropriately absorb bad news in a concurrent manner (e.g., Barberis, Shleifer, and Vishny, 1998), and the slow reaction of the market leads to continuing underperformance of financially distressed firms and eventually drives the medium-term continuation of stock returns.

3. Hypotheses

The presumed link between distress risk and size/value effect is summarized in the financial distress factor hypothesis suggested Chan and Chen (1991) and Fama and French (1992), in which they argue that the reason why higher stock returns are usually observed in small-sized firms or firms with equity is because these two types of firms are relatively financially distressed. In other words, the higher return is a compensation for the distress risk factor, and both small size and high book-to-market equity are just the two forms in which that risk factor is usually presented to the market: small-sized firms and firms with high book-to-market equity are likely to be financially constrained; in contrast, firm with large size and low book-to-market equity is conceived to be in a good financial condition.

Assuming that the explanation given by financial distress factor hypothesis to higher returns on small firms and firms with high book-to-market equity is correct, we would expect to continuously detect outperformance in distressed stocks over nondistressed stocks, even after taking control of size (book-to-market) factor; on the other hand, once controlling for distress risk, the size (book-to-market) effect should disappear: we would expect to see, for example, that in a group of distressed firms, firm with small capitalization (high book-to-market equity) would just do equally well as firms with large market capitalization (low book-to-market equity). The situation would be the same in a group of non-distressed firms. On this inference basis, we could have two null hypotheses tested, which are stated as follow:

- $H1_0$: Controlling for size (book-to-market) factors, distressed stocks will not anymore earn higher returns than non-distressed stocks do.

- $H2_0$: Controlling for the distress risk, small (high book-to-market) firms will continue to outperform big (low book-to-market equity) firms.

In order to accept the financial distress factor hypothesis of Chan and Chen (1991) and Fama and French (1992), we need to find evidence to reject these two null hypotheses. However, if in reality, the market tends to underreact to financial distress risk rather than gives compensation for that risk as suggested by Dichev (1998) and Cambell, Hilscher, and Szilagyi (2006) etc., we would instead observe lower return on distressed stocks than their equivalent non-distressed stocks. In addition, if the momentum effect is indeed attributed to distress risk as the consequence of the market's delayed reaction to that risk, that means momentum effect should have no chance to be observed in the firms with are not exposed to financial distress risk, therefore we would expect to see the market anomaly only appear among distressed stocks. These two market-underreaction-hypothesis-based expectations, consequently, lead us to another two null hypotheses as follows:

- $H3_0$: Distressed firms do not underperform non-distressed firms.

- $H4_0$: Medium-continuation of returns appears in both distressed stocks and non-distressed stocks.

Same as before, only if we are able to reject these two hypotheses, we would have evidence to support the arguments which Dichev (1998) Cambell, Hilscher, and Szilagyi (2006) and Agarwal and Taffler's (2008) stand up for.

4. Sample Selection and Data

This research is U.S.-based study. With the concern that the data analyses are mainly conducted on the portfolio basis, in order to get as sufficient amount of data for each portfolio group as possible, I made a combined use of stocks listed on the three U.S. stock exchanges, i.e. NYSE, AMEX and NASDAQ. However, the sample selection has to be restricted to the stocks with primary SIC Code 1-3999 and 5000-5999, to ensure that only manufacturing firms are involved in the analyses. The particular reason for this sample selection criterion is that the Altman's (1968) z-score model (Altman, 1968) was generated based accounting data of manufacturing firms, therefore, the correctness of the model's bankruptcy predictability is presumed to have certain industry limitation.[9] Moreover, since Altman's (1968) z-score model was initially designed for manufacturing firms with assets more than \$ 1 million, only those firms, size of which meets the lower bound, are included into the sample group.

Other three additional requirements for sample selection are concerned with the lower boundary of book value of a sample firm, the least stock listing period before portfolio formation and the least trading period after period formation, respectively:

1. The book value of all sample firms, which is computed as book value of equity (excluding preference capital) plus deferred taxes less minority interest from the latest available account needs to be positive. The main reasons are two: first, all the analyses of this study are conducted on portfolio basis, but firms with negative book value will become problematic when it comes to the need of assigning firms into different portfolios according to their book-to-market equity. Because in that case firms with negative book-to-market equity would be treated the same as low book-to-market firms, and therefore

[9] A more detailed introduction of Altman's z-score bankruptcy model will be given in the following section.

these two types of firms would most likely end up with being sorted into the same book-to-market quintile, regardless that their actual financial health statuses, presumably, are rather different from each other (Fama and French, 1992; Dichev, 1998).[10] Secondly, the logarithm of book-to-market will be needed in the Fama and MacBeth's (1973) cross-sectional regression analysis, but the logarithm calculation would be applicable only if the book-to-market measure is positive.

2. Sample firms are required to be listed for at least 24 months before the portfolio formation date. This criterion is mainly set for the purpose of portfolio's beta estimation, but another benefit from the pre-period of listing requirement is, it ensures that only post-listing accounting information, which is considered relevant in this study, will be used.

3. Furthermore, in order to prevent results from being affected by potential thin trading problem, a sample firm has to be traded in at least 9 of the 12 months subsequent to the portfolio formation.[11]

To ensure that the accounting variables are publicly available at the time of portfolio formation, a general approach is to assume a time lag between fiscal year-end date and the information releasing date. According to the U.S. Securities Exchange Commission (SEC) regulations, firms are required to file their 10-K reports with SEC within 90 days after their fiscal year ends.[12] Therefore, three-month lag is commonly assumed to be sufficient in earlier work (e.g., Basu, 1983). However, as reported by Alford, Jones, and Zmijewski (1992), there has been on average 19.8% found not strictly following the rules. In addition, among the December fiscal year-end

[10] Data is retested in time-series analyses with inclusion of firms with negative book-to-market ratio. The results are found to be with no primary change comparing to the original. The results are included in the Appendix I at the end of this paper.

[11] Thin trade is also commonly known as infrequent trading. It describes a condition in which there is little trading activity in a market because of a lack of buying or selling orders to drive up the volume. Due to high price volatility as the impact of low liquidity of infrequently traded stocks, thin trading can affect the results of empirical studies on efficiency by introducing serious bias into the results of empirical work. In addition, inferences drawn from tests of market efficiency are rendered imprecise in the presence of infrequent trading.

[12] A 10-K report is an annual report required by SEC, that gives a comprehensive summary of a public company's performance.

firms which do comply with the 90-day rule, 40% of them do the filing by the end of March, which make their reports become publicly available only until April. Alford, Jones, and Zmijewski (1994) also documented that 98 percent of the 10-K reports are filed by the end of the fifth month after fiscal year-end. For this reason, I made a conservative assumption of six-month lag between fiscal-end date and the information releasing date.[13] So, for example, the book value of equity and Z-score used for the portfolio formation on June 30, are derived from the latest available financial statements with fiscal year-end on or before previous year December 31.[14]

Samples are collected for 20-year span from June 1989 through June 2009[15] A further extension of the sample period is limited to the availability of data source.[16] But 20-year long period of data is believed to be a satisfactory base for conducting all the analyses of this study. Market index data (i.e. market return R_{Mt}, one-month T-bill rate R_{Ft}, return on size factor SMB_t and return on book-to-market factor HML_t) is retrieved from Professor Kenneth R. French's website. All accounting data and market data (share price) required in this study is collected from Thomson ONE Bank database. The majority of the data required for Altman's (1968) z-score calculation is collected from Thomson Financial database, but data resources from Worldscope database is also used as supplement. In the end, the final sample set constitutes 1878 manufacturing firms; and a total of 9137 firm years are qualified as sample firm years, 1184 of which are determined to be in financially distressed status by Altman's (1968) z-score (about 13%).

Table I below presents the descriptive statistics for all the variables of the interest in this study. It is meant to give a general picture of the empirical distribution of the test variables, and meanwhile provide statistical information which can be used to make a comparison with other studies in the same field. For example, Dichev (1998) in his study provided a similar type of

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[13] The same assumption was also made in Fama and French's (1992) study.

[14] Due to the fact that over 75% of sample firms are found to have their fiscal year-end day on December 31, I chose June 30 as the portfolio formation date for this study.

[15] Accounting data collection starts from 1988's fiscal-year end; the last firm stock price is taken on 3oth of June 2009.

[16] Some required items e.g. Market Capitalization is found only available from late 80's onward in Thomson Financial.

descriptive statistics on U.S. data from a different sample period, despite that not all items investigated are exactly the same as in this paper.[17] Some differences in the empirical distribution of those test variables are found by comparing the common items presented in both Table I and Dichev's (1998) table. For example, on average, firm's market capitalization is shown higher in this study than in Dichev's (1998) paper; so is the figure at each of the 5th, 25th, 50th, 75th and 95th

Table I

Descriptive Statisticsfor the Test Variables

This table presents the descriptive statistics to illustrate the empirical distributions of the test variable. Size is the log of fiscal year-end market value of equity calculated as share price multiplied by shares outstanding. B/M is book-to-market ratio, which is computed as the fiscal year-end book value of equity (excluding preference capital) plus deferred taxes less minority interests and then divided by the market value of equity on June 30. Prior-Year Return is defined as the 11-month return from July 1 of year $t-1$ to May 31 of year t. Z-Score is the measure of bankruptcy risk obtained from Altman's (1968) z-score model. Monthly Return is the subsequent-year (from July of year t to June of year $t+1$) average monthly stock logarithm return for the combined sample of NYSE, AMEX, and Nasdaq firms. Std. is the standard deviation of the concerned variable. And the value at 5th, 25th, 50th, 75th and 95th percentiles in each variable distribution are presented under item P5, P25, P50, P75 and P95 respectively. For all variables excluding Size, the smallest and the largest 1% observations are set to 0.01 and 0.99 percentiles accordingly.

Variables	mean	Std.	P5	P25	P50	P75	P95
Size	6.85	2.01	3.26	5.62	6.92	8.14	10.16
B/M	0.47	0.43	0.03	0.16	0.37	0.63	1.28
Prior-Year Return	8.05	36.38	-50.89	-10.53	8.49	26.89	63.12
Z-Score	4.41	3.25	1.42	2.58	3.65	5.21	9.78
Monthly Return	-0.07	3.45	-5.98	-1.72	0.11	1.83	5.03

percentile of the Size variable's distribution. On the other hand, sample firms in this study tend to have both lower mean value and lower value at presented percentiles for book-to-market ratio. However, these differences are considered to be understandable and acceptable, since although both this and Dichev's (1998) studies are based on U.S. market, the focused periods are not

[17] The empirical distribution information on Ohlson's O-Score (1980) was provided in Dichev's (1998) table, but it is left out in this study as Ohlson's O-Score (1980) is not used to determine sample firm's financial health status, therefore not a variable of interest. On the other hand, Table I additionally provides the distribution information on stock's prior-year return, a variable to which a big proportion of the later analyses and discussions are devoted in the context of examining the link between distress risk and the momentum effect.

exactly overlapping with each other that while Dichev's data collection covered a period from 1981 to 1995 the sampling year in this study is from 1989 through 2008. As the whole capital market met a fast development in the past two decades, it is reasonable to presume for decent growth in size on an individual level along with the aggregate growth of the economy. Furthermore, based on the way how the book-to-market ratio is calculated, the lower figure for that item is very likely to be just one of the consequences of the growth of firm's market value of equity during the period.

Since Altman's (1968) z-score is used as the base of this study to determine a sample firm whether is at bankruptcy risk or not, it is very important to ensure that both the accounting and market information used to calculate the Altman's (1968) z-score are accurate and the z-score obtained for each sample firm is reliable. Indeed, even if it is possible, an exact data accuracy checking on individual level is a rather complex process and therefore would require a mass of effort. A rough but more efficient way to figure out whether the obtained Altman's (1968) z-sore is convincing enough to be used for the research purpose is to get some statistical information about the results, such as statistical distribution of all sample firm's z-scores, and see whether we are able to find its empirical supports from other studies. But unfortunately, there is not any other research paper that I've searched from providing the type of information about Altman's (1968) z-score in the same manner as it is provided in Table I, except for Dichev's (1998) paper. However, even if given that the information about the statistical distribution of sample firms' Altman's (1968) z-scores is available in Dichev's (1998) paper, in author's opinion, a comparison between the figures provided in Dichev's (1998) and the current study might still not be able to solve the original question: the difference in the mean and value at each quintile[18] might be due to the noise in the accounting data which the z-score calculation is based on in this study, but it might also just purely due to the different sampling period considered in the two studies.

[18] The statistical distribution of sample firms' z-scores provided in Dichev's (1998) study is as follow: the value is 5.31, 7.71, 0.23, 2.37, 3.56, 5.41 and 15.39 for mean, standard deviation, the 5th, 25th, 50th, 75th and 95th percentile, respectively. As we can see, the difference between some of the figures and those exhibited in Table I is quite noticeable (e.g., the value at 95th percentile) while others are minor (e.g., the value at 50th percentile).

Fortunately, although without any exact figure comparison, a rough picture could still be provided to help us see whether the base provided by the calculated Altman's (1968) z-score in this study is sensible or not by an investigation on the change in the proportion of firms estimated to be at distress risk along with a dynamic economic condition. Knowing that change in macroeconomic condition would have a large impact on microeconomic level, making an assumption of a positive correlation between a firm's financial health condition and periodical fluctuation in economy sounds reasonable. That is, a firm is more easily to become financially distressed in an economic recession, but less likely to encounter the same problem during an economic boom. Following this thought, we would expect to see the proportion of total firms in the market falling into financial distress decrease during years in which the economy is moving upwards; in contrast, the percentage will increase when the whole economy is in its downturn.

As one of the three monetary tools which governments commonly use to control the growth and stability of economy, federal interest rate's movement is always committed to a close link with the change in economic situation at the time. Usually, government tends to set relatively high federal interest rate during economic boom to prevent its country from unhealthy inflation; but during an economy depression, on the other hand, government often takes just the opposite action – lowers federal interest rate to help to stimulate economic activities. Figure 1.1 exhibits two graphs: the dashed line presents the movement of the one-month Treasury bill rate from 1989 to 2008 and the solid line presents the change in the amount (presented in percentage) of sample firms whose Altman's (1968) z-scores fall below the cutting-off point 1.81 during the same period. As we can see, the two graphs tend to consistently move towards opposite direction over time. For example, when federal interest rate was set at a relatively high level between year 1995 and 2000, implying an economic booming at the time, the percentage of sample firms with Altman's (1968) z-score lower than 1.81 was on its low side; but when federal interest rate was kept at its lowest level during recession year 2003 and 2004, the percentage of sample firms with Altman's (1968) z-score lower than 1.81 is seen move toward the height. In a word, the dynamic change of two factors shown in Figure 1.1 suggests that the proportion of sample firms becoming financially distressed ($z<1.81$) is oppositely affected by the change in economic condition, which is just like what we expected. Therefore, on this basis, it allows us to conclude that the calculation of Altman's (1968) z-score is based on appropriate accounting and market information, and the final results obtained should provide a reasonable and reliable base to conduct the core analyses of this study.

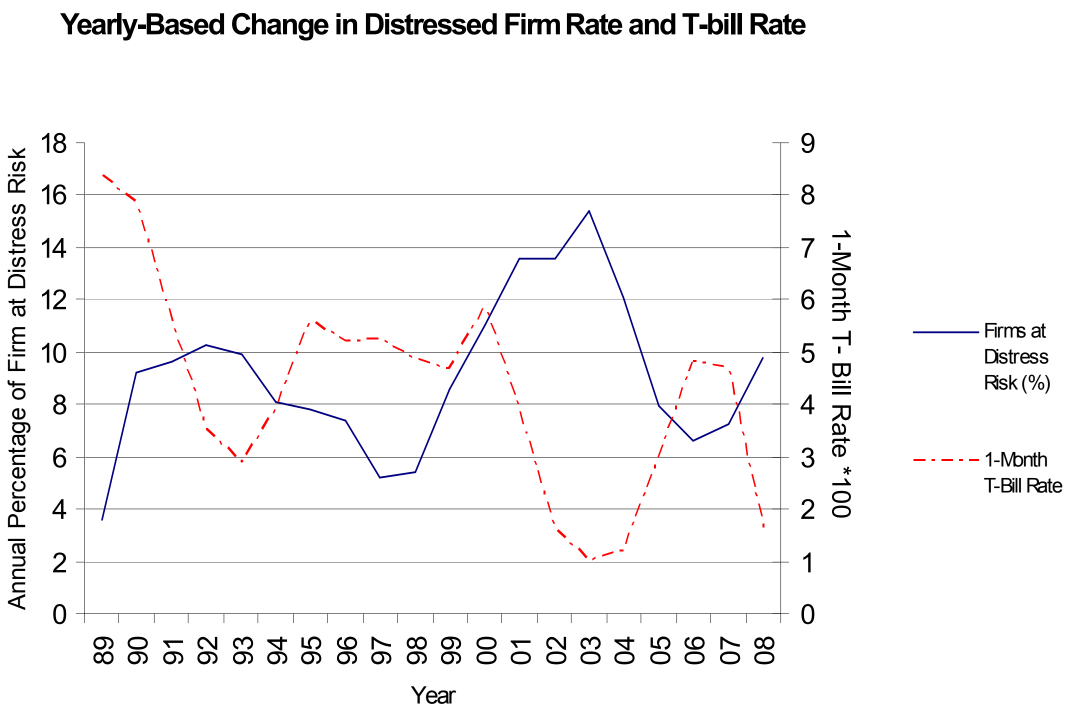

Figure 1.1

5. Methodologies

In this section, the portfolio formation method and cross-sectional regression analyzing method applied in this study will be given a detailed description, respectively. But before moving on to that stage, I would like to give a brief introduction of Altman's (1968) z-score bankruptcy predicting model due to the important role that the model plays both in general and in this particular study: first, this model is one of the earliest models designed for uncovering bankruptcy potential of a business, and is by far the most extensively referred in subject-related empirical research and used in bankruptcy prediction in practice; second, because the conclusions made in this study will rely on a series of comparisons between the results obtained for z-score-determined distressed portfolios and the results obtained for their equivalent non-distressed portfolios, choosing a specific model to provide the distress risk determination basis will certainly affect the analytical results of this study, and therefore also have impact on the final conclusion to be drawn.[19]

5.1. Introduction to Altman's (1968) Z-Score Model

With the recognition of the shortcomings of the traditional ratio analysis as a technique for investigating corporation performance, Altman (1968) introduced an accounting-based discriminant analysis model – z-score model, of which the emphasis centers on its compatibility with ratio analysis in a bankruptcy prediction context.[20] Based on the original version of the model, Altman's (1968) z-score is computed by adding up four common accounting ratios with different weight:

$$z = 1.2x_1 + 1.4x_2 + 3.3x_3 + 0.6x_4 + 0.99x_5 \tag{1}$$

where

x_1 = working capital / total assets

x_2 = retained earnings / total assets

x_3 = earnings before interest and taxes / total assets

x_4 = market value of equity / book value of total liabilities

x_5 = sales / total assets

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[19] Besides that the market and period which this study is based on is different from what was considered in Agarwal and Taffler's (2008) paper, another big difference between these two studies is the bankruptcy predicting model used to draw the line between distressed firms and non-distressed firms. Ever since the very first z-score bankruptcy predicting model was established by Altman (1968), there have been many other specific country-based or industry-based versions of the model proposed in later studies (Altman, 1973; Altman et al, 1974; Frederikslust, 1978; Sinkey, 1979; Matolcsy, 1981 etc.). All the existing z-score bankruptcy predicting models were established on accounting-ratio basis and derived uniformly using a discriminant modeling approach. But due to the fact that each concentrated area of a model possesses distinctive characteristics, the effective discriminant factors considered in each model as well as their assigned weight are therefore different from one version to another. While the UK-based z-score model of Taffler (1983, 1984) and Agarval and Taffler (2007) was employed in Agarwal and Taffler's (2008) study, the Altman's original z-score bankruptcy predicting model, however, is considered to be more appropriate to be used in this study due to its U.S.-market-basis.

[20] The essential idea of discriminant technique is to distinguish between two or more distinct populations on the basis of certain of the characteristics of their members, and therefore help to classify further individuals as belonging to one of the populations more than any of the others.

The evidence based on 66 sample observations in Altman's (1968) paper shows, firms with z-score above 2.99 are generally in good, or at least normal financial health condition, therefore the z-score area which is above the 2.99 point is defined as the "safe zone". On the other hand, most of the firms with z-score below 1.81, are found eventually gone to bankruptcy within two years, hence the z-score area which is below the 1.81 point is considered as a dangerous area, meaning it is very likely that any firm falling in that area is at financial distress risk at the time, which might even leads the firm to bankruptcy in the near future. As to the area between 1.81 and 2.99, it is called "the zone of ignorance" or "grey area", because according to Altman (1968), the actual financial status seems still left unclear for the firms with z-score within that range, therefore it is hard to make a prediction whether those firms will go bankruptcy or not in the near future. Furthermore, as the generation of the original model was solely based on firm data in the manufacturing sector, it was notified particularly in the paper that, the application of this set of standards is only limited to manufacturing corporations.[21]

In the initial test, Altman's (1968) z-score showed a rate of 72% in accuracy in predicting bankruptcy in two-year time, with Type II error (classifying the firm as bankrupt when it does not go bankruptcy) of 6% (Altman, 1968). Later on, Altman's (1968) z-score's predicting power was repeatedly retested using different time period data in other research papers (e.g., Begley, Ming and Watts, 1997; Grice and Ingram, 2001)[22] in addition to the retesting conducted by Altman himself. After a series of subsequent tests, the model was found to be approximately 80-90% accurate in predicting bankruptcy one year prior to the event, with a Type II error of approximately 15-20% (Altman, 2000). As a result of its outstanding bankruptcy predicting capability, since middle 80's, the Altman's (1968) a-scores started to gain wide acceptance in the

[21] Nevertheless, Altman's (1968) model finds to be still conventionally been applied across the spectrum of firms from other sectors, as mentioned in Agarwal and Taffler (2007). The only exceptions are financial institutions. Same as other balance sheet-based models, Altman models are not recommended to be used to assess financial corporations, because of the intransparent feature of financial corporations' balance sheets and their frequent use of off-balance sheet items.

[22] Begley, Ming and Watts (1996) confirm the predictive ability of Altman's Z-Score on firms in 80's. Meanwhile, they show the predictive ability could not be further improved with a re-estimation of the model using updated data. Grice and Ingram (2001) test the effectiveness of this bankruptcy predicting model on non-manufacturing firms. Their result suggests that the original Altman's Z-score model is not as useful for predicting bankruptcy of non-manufacturing firms as it is for predicting bankruptcy of manufacturing firms.

practical world (e.g., by auditors, management accountants, courts, and database systems used for loan evaluation). [23]

5.2 Portfolio Formation

The investigations of the relation between distress risk and the three market anomalies, i.e. size effect, book-to-market effect and momentum effect are first taken on a univariate level. In each one of the three investigations, ten portfolios are formed on two-way sorts on one of the three factors (firm size, book-to-market equity and prior-year return) and z-score. More specifically:

1. When examining the relation between size effect and distress risk, firms are ranked on their market capitalization on June 30 of each year and grouped into five portfolios with approximately equal numbers of stocks in each. Next, all the firms are independently sorted into two "financial health status" portfolios: the healthy group – the one includes all firms with z-score above 1.81; and another problem group – the one consists of all firms with z-score below 1.81. Ten portfolios are then formed at the intersections of market capitalization and z-score.

2. When examining the relation between book-to-market effect and distress risk, firms are ranked on their book-to-market ratio on June 30 of each year and grouped into five portfolios with approximately equal numbers of stocks in each. [24] Next, all the firms are independently sorted into two "financial health status" portfolios: the healthy group – the one includes all firms with z-score above 1.81; and another problem group – the one consists of all firms with z-score below 1.81. Ten portfolios are then formed at the intersections of book-to-market ratios and z-score.

[23] Altman (2000) did have further developed two specific versions of Z-score model for both privately held firms (the Altman Z'-Score) and non-manufacturers (the Altman Z'-Score) respectively. However, in order to limit the unnecessary complexity in data analysis, those two versions of Z-score model are not considered in this study.

[24] Throughout this paper, book-to-market ratio is computed as book value of equity excluding preference capital plus deferred taxes less minority interests, which are available in sample firms' the latest financial statement with fiscal year-end on or before December 31, and the market value of equity is the market data taken on the portfolio formation day June 30.

3. When examining the relation between momentum effect and distress risk, firms are ranked on their prior 11-month returns (i.e. July 1 of year t-1 to May 31 of year t) on June 30 each year, and grouped into five portfolios with approximately equal numbers of stocks in each. Next, all the firms are independently sorted into two "financial health status" portfolios: the healthy group – the one includes all firms with z-score above 1.81; and another problem group – the one consists of all firms with z-score below 1.81. Ten portfolios are then formed at the intersections of prior-year returns and z-score.

Besides applying the two-way sorting methodology during the univariate analyses, a more complicated four-way sorting method is employed for a more sophisticated cross-sectional analyzing purpose. Based on this method, twenty four portfolios are formed at the intersections of firm size, book-to-market equity, prior-year return and z-score. More specifically, at the end of June of each year from 1989 through 2008, all the sample firms are ranked on market capitalization and grouped into two portfolios using median as the break point; they are then independently ranked on B/M, and grouped into three portfolios: one with lowest 30%, one with the middle 40% and one with 30% highest B/M ratio; the same ranking process is also done to all the samples on the base of prior-year return, and they are grouped into two portfolios using median as the break point; finally, all firms are independently allocated to two groups based on whether their latest available z-score before portfolio formation day is smaller or larger than 1.81. Twenty-four portfolios are then constructed at the intersection of size, B/E, momentum, and z-score. Portfolios are rebalanced at the end of June each year during the entire sample period.

5.3 Regression Analysis

In the series of univariate analyses, Fama and French (1993) three-factor regression model is employed to examine the various portfolios' performances on risk-adjusted basis. Since this factor-based model is one of the most widely used model to predict a stock's behavior on risk-adjusted basis, the constant obtained from the analysis therefore should be able to disclose a portfolio's ability of earning superior return after risk adjustment:

$$R_{it} - R_{Ft} = \beta_1 + \beta_2 (R_{Mt} - R_{Ft}) + \beta_3 SMB_t + \beta_4 HML_t \varepsilon_{it} \tag{2}$$

where

R_{it} = the equally weighted return on portfolio i during month t;

R_{Ft} = the one-month T-bill rate at the beginning of month t, information is available on Professor Kenneth R. French's website;

R_{Mt} = the value-weighted return during month t, information is available on Professor Kenneth R. French's website;

SMB_t = the return on the mimicking portfolio for the size factor during month t – information is available on Professor Kenneth R. French's website;

HML_t = the return on the mimicking portfolio for the B/M factor during month t – information is available on Professor Kenneth R. French's website;

ε_{it} = a mean-zero stochastic error term.

In addition, a more sophisticated analysis on the link between momentum effect and financial distress risk is conducted later in this study through Fama and MachBeth (1973) cross-sectional regression analysis. Following Agarwal and Taffler (2008), the regression model is an extended version of a three-factor-based model with three additional variables (prior-year monthly average return, dummy variable Z-score and an interaction dummy of the former two). Specifically:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}\ln(size_{it-1}) + \gamma_{3t}\ln(B/M_{it-1}) + \gamma_{4t}Mom_{it-1} + \gamma_{5t}z(0/1)_{it-1} + \gamma_{6t}z(0/1)_{it-1} * Mom_{it-1} + \varepsilon_{it} \tag{3}$$

where

R_{it} = the equally weighted return on portfolio i during month t;

R_{Ft} = the one-month T-bill rate at the beginning of month t, information is available on Professor Kenneth R. French's website;

β_{it-1} = the beta of portfolio i estimated at the portfolio formation date[25] [26];

[25] Portfolio betas are the sum of slopes in the regression of the return on a portfolio on the current, prior, and next month's market returns. One lead and one lag are considered to reduce problems of thin trading Dimson (1979). The estimation is based on the two-year monthly stock returns on firms in the portfolio prior to the portfolio formation.

$\ln(size_{it-1})$ = the natural logarithm of average market capitalization of common equity of stocks in portfolio i at the portfolio formation date;

$\ln(B/M_{it-1})$ = the natural logarithm of the average of B/M ratios of stocks in portfolio i at the portfolio formation date[27];

Mom_{it-1} = the average monthly raw return over the 11 months from July year $t-1$ to May year t for all stocks in portfolio i;

$z(0/1)_{it-1}$ is a dummy variable indicating a financial health status with 0 if Altman's (1968) z-score is less than 1.81, 1 otherwise; and,

$z(0/1)_{it-1} * Mom_{it-1}$ is an interaction dummy between momentum and Z-score

It is worth noting that, in Agarwal and Taffler's (2008) model the nature logarithm of book-to-market equity ($\ln(B/M)$) is included as an explanatory variable. The conduction of the model is based on Fama and French's (1992) and Jagadeesh and Titman's (1993) study. However, the use of $\ln(B/M)$ as seen in Fama and French's study is specifically criticized by Dichev (1998). Noting the positive/negative book value dichotomy as an explicit prediction variable in Ohlson's (1980) model, Dichev (1998) believes that firms with negative book value are highly likely to be at bankruptcy risk. The problem with using $\ln(B/M)$ as a variable in a regression model is that the measure becomes invalid for firms with negative book value, and for that reason they have to be excluded from the sample which will be used in the regression analysis. Dichev (1998) does have a point in terms of the use of $\ln(B/M)$, because it is obvious that whenever a regression model is designed for a purpose of studying financial distress risk, eliminating firms with high distress risk from the sample is not quite appropriate.

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[26] Throughout this paper, subscript t represents time of portfolio formation and subscript $t-1$ shows that the information is available at the time of portfolio formation.

[27] For the detailed computation explanation for the B/M ratio, please see Footnote 22.

6. Results

In this section, the market reaction to distress risk and relationship between distress risk and the three market anomalies, namely the size effect, the value effect and the momentum effect will be investigated in the context of sample-based tests of null hypothesis $H1_0$ through $H4_0$ respectively. Firstly, the statistical information on the samples of this study is provided. Then it is followed by the presentation and discussion on the results obtained from a series of univariate analyses. A detailed discussion on the results obtained from Fama and MachBeth (1973) cross-sectional regression analysis is held in the end of this section.

6.1. Preliminary Results

As a starting point of examining how distress risk is related with size, book-to-market factor and previous return, Table II provides us some information about three sets of sample distribution of financially distressed firms in five groups which are obtained following a factor-based order. The information delivered by the table can be summarized as follow: First, it is clearly shown in Panel A that there is 20.83% of the sample firms in the smallest size group determined to be at financial distress risk. That percentage is much higher than it is in the other four portfolios. Second, we also find in Panel B that, the biggest proportion of distressed firms falls into the portfolio group with the highest book-to-market equity (20.15%). Third, when portfolios are sorted based on firm prior-year stock return (Panel C), 322 out of 1829 firms (16.79%) in the lowest prior-year return portfolio are determined to be financially distressed. That percentage is the highest among the five portfolios as exhibited in Panel C.

Overall speaking, although lacking of formal statistical significance test, the results given in Table I provide us some preliminary evidence on the relation between financial distress risk and firm size, book-to-market and prior-year return: compared with firms in bigger size, smaller firms seem more likely to fall in a financial distressing problem; and so are firms with higher book-to-market equity compared to those firms with lower ratio. Additionally, prior-year return seems to be associated with financial distress risk as well, in a way firms at distress risk are more likely to

Table II

Financial Distress Rate in Two-Way Sorted Portfolios

Portfolios in Panel A are formed as follows: Firms are ranked on their market capitalization on June 30 of each year from 1989 to 2008, and grouped into five portfolios with approximately equal numbers of stocks in each. Then, all firms are also independently sorted into two "financial health status" portfolios: the healthy group – the one includes all firms with z-score above 1.81; and another problem group – the one consists of all firms with z-score below 1.81. Ten portfolios are then formed at the intersections of market capitalization and z-score. Portfolios in Panel B are formed as follows: Firms are first ranked on their book-to-market ratio on June 30 of each year from 1989 to 2008, and grouped into five portfolios with approximately equal numbers of stocks in each. The book-to-market ratio is computed as the ratio of previous fiscal year-end book value of equity excluding preference capital plus deferred taxes less minority interests, divided by the market value of equity on June 30 in current year. Then, all firms are independently sorted into two "financial health status" portfolios: the healthy group – the one includes all firms with z-score above 1.81; and another problem group – the one consists of all firms with z-score below 1.81. Ten portfolios are then formed at the intersections of book-to-market ratios and z-score. Portfolios in Panel C are formed as follows: on June 30 each year from 1989 to 2008, firms are ranked on their prior 11-month returns from July 1 of year t-1 to May 31 of year t and grouped into five portfolios with approximately equal numbers of stocks in each. Then, all firms are independently sorted into two "financial health status" portfolios: the healthy group – the one includes all firms with Z-score above 1.81; and another problem group – the one consists of all firms with Z-Score below 1.81. Ten portfolios are then formed at the intersections of prior-year returns and Z-Score.

	Distribution of Firms		% of Firms with Z < 1.81
	Z < 1.81	Z > 1.81	
Panel A. Size and z-Score Portfolios			
Small	381	1448	20.83%
2	223	1606	12.19%
3	216	1613	11.81%
4	189	1640	10.33%
Big	175	1646	9.61%
	1184	7953	12.96%
Panel B. B/M and z-Score Portfolios			
Low	307	1522	16.79%
2	169	1660	9.24%
3	137	1692	7.49%
4	204	1625	11.15%
High	367	1454	20.15%
	1184	7953	12.96%
Panel C. Prior-Year Returns and z-Score Portfolios			
Low	322	1507	17.61%
2	216	1613	11.81%
3	174	1655	9.51%
4	189	1640	10.33%
High	283	1538	15.54%
	1184	7953	12.96%

earn lower return before the information needed for determining their true financial status at the time (information required for z-score calculation) becomes publicly available. While it is very possible that there have already been signals in the market conveying the same message, the market does not seem to take them very seriously, and therefore does not react accordingly. On the other hand, if the Altman's (1968) z-score is widely accepted as being very effective in bankruptcy prediction, then an interesting question is whether would this underperformance be continued (a positive correlation between prior-year return and current return) even after Altman's (1968) z-score of financially distressed firms becomes public information? Moreover, from the fourth column of Table I where the proportion of total sample firms determined to be at distress risk is presented in percentage, we notice that except for the size factor (Panel A), the proportion of sample firms which are at distress risk does not change along with the increase or decrease in firm's book-to-market equity and prior-year return, respectively, in a monotonic way. For this reason, it would be too careless to draw a conclusion on the relation between distress risk and the three factors of interest based on the information about the distribution of distressed sample firms provided in Table I. Instead, a formal correlation test should help us see a clearer picture.

A Pearson's Correlation analysis is conducted on all concerned variables on the individual-firm basis and the results are demonstrated in Table III. First of all, the relationship between stock return and size and book-to-market equity these two factors which has been loudly-argued in previous studies get firmly confirmed by the correlation test results shown in the table. In brief, the coefficient -0.055 and 0.101 tell us that a firm's stock return is negatively correlated with its firm size but positively correlated with its book-to-market equity.

Secondly, as for what has been found on the correlation between distress risk and other factors of interest, we can see that a positive correlation between size factor and z-score is shown in the table, implying that smaller firms tend to be at higher distress risk. Although the obtained coefficient (0.062) is relatively small in its absolute value, it differs from zero above 1 percent significant level, and the result is also comparable with empirical test result reported in other studies (e.g., Dichev, 1998). On the other hand, book-to-market equity is shown to be negatively correlated with z-score by a coefficient of -0.207 of which the statistical significance level is above 1 percent, meaning that the higher the book-to-market ratio a firm has, the more likely that firm is facing a financial distress problem. Despite of the different studying period concentrated, this result is quite close to that is reported in Dichev's (1998) paper, where a coefficient of -0.216 was obtained for the correlation test between the two test variables. Moreover, a positive coefficient 0.002 suggests that the prior-year return is positively correlated with z-score, meaning that the higher the likelihood that a firm is at distress risk, the lower the prior-year stock return is

Table III

Pearson Correlation Coefficients for the Test Variables

This table presents Pearson's Correlation matrix for all test variables based on the study sample of 9137 firms. Size is the log of fiscal year-end market value of equity calculated as share price multiplied by shares outstanding. B/M is book-to-market ratio, which is computed as the fiscal year-end book value of equity (excluding preference capital) plus deferred taxes less minority interests and then divided by the market value of equity on June 30. Prior-Year Return is defined as the 11-month return from July 1 of year $t-1$ to May 31 of year t. Z-Score is the measure of bankruptcy risk obtained from Altman's (1968) z-score model. Monthly Return is the subsequent-year (from July of year t to June of year $t+1$) average monthly stock logarithm return for the combined sample of NYSE, AMEX, and NASDAQ firms. For all variables excluding Size, the smallest and the largest 1% observations are set to 0.01 and 0.99 percentiles accordingly. Panel B displays a Pearson correlation matrix for all test variables. Figures in parentheses are the t-statistics.

Correlation	**Size**	**Book-to-Market Ratio**	**Prior-Year Return**	**Z-Score**	**Average Monthly Return**
Size	1.000*** (infinity)				
B/E ratio	-0.163*** (15.79)	1.000*** (infinity)			
Prior Year Return	-0.009 (-0.86)	-0.170*** (-16.49)	1.000*** (infinity)		
Z-Score	0.062*** (5.94)	-0.207*** (20.22)	0.002 (0.19)	1.000*** (infinity)	
Average monthly return	-0.055*** (-5.265)	0.101*** (9.70)	-0.001 (-0.10)	-0.037*** (-3.54)	1.000*** (infinity)

*** Significant at or above the 0.01 level
** Significant at the 0.05 level
* Significant at the 0.10 level

expected to be found on that firm. However, it is worth noting that, although if been looked at independently, the positive coefficient is a confirmation on the relation between prior-year return and distress risk which is implied based on the results given in Table II Panel C, the low *t*-test result (t = 0.19) presented in the parenthesis below suggests that the estimated coefficient risk is not significantly different from zero, and therefore makes the above conclusion less clear.

Among others, the correlation between distress risk and stock return needs particular attention. By looking at the table, we notice that the correlation between distress risk and stock return is shown to be negative (-0.037), and statistically significant at the 1 percent level (t = -3.54). Based on this result, a negative answer seems to have been given to the previous question that whether this underperformance would be continued even after Altman's (1968) z-score of financially distressed firms becomes public information. The implication underlying the negative correlation between financial distress risk and average monthly stock return is that when doing asset pricing, market has taken distress risk into account as a systematic risk, therefore firms with higher distress risk are compensated with higher return than that on financially healthy firms. This result seems to be a disapproval of the market underreatction story stood on by e.g. Beaver (1968), Dichev (1998) and Campbell, Hilscher and Szilagyi (2006). But it is too early to make any conclusion yet. A negative correlation between distress risk and stock return was also found in Dichev (1998) in his correlation test. The coefficient of -0.009 was obtained to indicate the correlation between Altman's (1968) z-score and stock return in that paper. However, even if this was given first, later in the same paper an opposite conclusion was made on the relation between distress risk and stock return based on results obtained through a series of more sophisticated cross-sectional analyses. Therefore, on this basis, the link between distress risk and stock return does seem to require deeper analysis before any conclusion is made.

Last but not least, although momentum effect has been widely observed and reported in many other researches as well as in practice, an expected positive correlation between the prior and current return is not found based on the sample of this study. Instead, the correlation examined between the two returns is negative and rather small (-0.001), but the result is determined to be not significantly different from zero (t = 0.86). Therefore, statistically speaking, there is not any autocorrelation found between stock's prior and current return. There are two possible explanations for this result: it could be just like it has shown that the momentum effect does not exist among the sample firms; it is also possible that the momentum effect among the sample firms is only moderate and only exists among firms which share some certain characteristics such as being at financial distress risk, but due to the relatively small number of that kind comparing to the total sample size, the momentum effect is eventually dissolved when the examination is undertaken on the entire sample.

To summarize this section, our empirical investigation so far has obtained us some insights into the relationship between distress risk and other three factors (i.e. firm size, book-to-market ratio and stock return). Besides being confirmed that higher stock returns are earned by smaller firms and firms with higher book-to-market equity, the correlation test results are found to be supportive to the previously claimed negative relationship between distress risk and firm size factor and positive relationship between distress risk and book-to-market factor (e.g. Chan and Chen, 1991; Fama and French, 1992). Moreover, the test results also give us some hint on the relationship between distress risk and stock return. These preliminary results have provided a solid ground from which further examinations on the relation between distress risk and size effect or value effect or momentum effect can be conducted. For instance, if small firms and value firms are likely to have higher distress risk, and at the same time the same firms tend to earn higher stock returns, then whether the higher stock returns on small and value firms can be explained by the higher distress risk embedded in those firms (financial distress factor hypothesis of Chan and Chen, 1991; Fama and French, 1992)? Also, correlation between z-score and stock return is found statistically insignificant, and so is the autocorrelation between current stock return and prior-year return. These two findings together have left question mark on the pre-claimed distress-risk-related stock underperformance and its link with momentum anomaly (Beaver, 1968; Dichev, 1998; Campbell, Hilscher and Szilagyi, 2006). Next section will concentrate on examining the series of questions aroused here and attempt to provide some clear answers to those questions through more sophisticated methodologies applied.

6.2. Univariate Analysis

In this section, a series of univariate analysis will be conducted to examine the link between distress risk and the three market anomalies, i.e. size effect, value effect and momentum effect.

6.2.1 Test on Distress Factor Hypothesis

As mentioned in the former section, according to Chan and Chen (1991) and Fama and French (1992), firm size and book-to-market equity are two functioning proxies for distress risk; higher returns on smaller firms and firms with higher book-to-market equity are eventually a compensation for that systematic risk. If this distress factor hypothesis is correct, we would expect to see that, even after controlling for firm size (book-to-market) factor, financially distressed firms will still outperform non-distressed ones. On the other hand, once distress risk factor has been taken control, the size (book-to-market) anomaly (i.e. small-market-capitalization/high-B/M stocks outperform big-market-capitalization/low-B/M stocks) will disappear. Following this thought, two null hypotheses ($H1_0$ and $H2_0$) are established to test the distress risk factor proposition.

- $H1_0$: Controlling for size (book-to-market) factors, distressed stocks will not anymore earn higher return than non-distressed stocks do.

- $H2_0$: Controlling for the distress risk, small (high book-to-market) firms will continue to outperform big (low book-to-market) firms.

Table IV presents the analysis results of returns on ten portfolios formed on two-way sorts on size and z-score. Panel A of Table IV first provides the summary statistics on the portfolios. Then portfolio returns further examined on risk-adjusted basis through Fama and French (1993) three-factor regression analysis, and the results are summarized in Panel B of Table IV.

Some descriptive statistics are exhibited in the first few columns in the table in Panel A for the ten portfolios. Taking a glance on the figures, two facts regarding the subgroup samples' size and

Table IV

Size and Distress Risk in Stock Returns

Portfolios are formed as follows: at the end of June of each year from 1989 to 2008, all the stocks in the sample are allocated to two groups based on whether their latest available z-score is smaller or larger than 1.81. The stocks are also independently ranked on market capitalization and grouped into five portfolios. Ten portfolios are then formed at the intersections of size and z-score. For each size quintile, an arbitrage portfolio labeled "Difference," long on distressed stocks and short on non-distressed stocks, is also formed. Panel A presents the portfolio summary statistics. B/M is computed as the ratio of book value of equity (excluding preference capital) plus deferred taxes less minority interests from the latest available accounts divided by the market value of equity on June 30. Average monthly excess return is the time-series average of difference between monthly stock returns and the one-month Treasury bill rate observed at the beginning of the month. Portfolio betas are the sum of slopes in the regression of the return on a portfolio on the current, prior, and next month's market returns. Average size, average B/M, and average momentum are the time-series averages of monthly averages of market capitalization, B/M, and prior 11-month returns (excluding June), respectively, for stocks in the portfolio at the end of June of each year. Panel B presents the intercepts and adjusted R^2 for each of the portfolios from the following Fama and French (1993) three-factor model (Equation 2):

$$R_{it} - R_{Ft} = \beta_1 + \beta_2 (R_{Mt} - R_{Ft}) + \beta_3 SMB_t + \beta_4 HML_t \varepsilon_{it}$$

where R_{it} is the equally weighted return on portfolio i during month t, R_{Ft} is the one-month Treasury bill rate at the beginning of month t, and R_{Mt} is the value-weighted return during month t. Here SMB_t is the return on the mimicking portfolio for the size factor during month t, and HML_t is the return on the mimicking portfolio for the B/M factor during month t. Also, ε_{it} is a mean-zero stochastic error term. Data for variables R_{Mt}, SMB_t and HML_t are all taken from taken from Professor Kenneth R. French's website. Figures in parentheses are the t – statistics.

Panel A. Summary Statistics

Size	Average Market Cap ($m)		Average B/M		Average Monthly Prior-Year Return (%)		Average Beta		Average Excess Monthly Returns (%)		Difference
	z<1.81	z>1.81	z<1.81	z>1.81	z<1.81	z>1.81	z<1.81	z>1.81	z<1.81	z>1.81	
Small	65.80	80.76	0.91	0.74	2.18	1.42	1.29	1.13	2.08**	1.40***	0.68
									(3.63)	(4.20)	(1.60)
2	415.06	385.30	0.70	0.56	1.23	1.17	1.44	1.41	1.11**	0.96***	0.15
									(2.54)	(2.90)	(0.51)
3	966.32	971.62	0.61	0.43	1.48	1.33	1.30	1.16	0.46	0.68**	-0.18
									(1.62)	(2.75)	(-0.83)
4	2548.93	2546.38	0.57	0.35	1.10	1.33	1.27	1.14	0.65	0.59**	0.06
									(1.52)	(2.55)	(0.20)
Big	41677.73	21927.12	0.47	0.25	1.11	1.35	0.96	0.80	0.46	0.44*	0.03
									(1.47)	(1.81)	(0.12)
Small-Big									1.62***	1.05***	0.66
									(3.14)	(3.52)	(1.47)

Table IV

Size and Distress Risk in Stock Returns (Continued)

Panel B. Fama and French (1993) Regression Results

Size	Intercept (β_1)			Adjusted R^2		Difference
	z<1.81	z>1.81	Difference	z<1.81	z>1.81	
Small	1.37**	0.54**	0.85	0.20	0.63	0.01
	(2.18)	(2.16)	(1.57)			
2	-0.34	-0.33	-0.07	0.57	0.78	0.06
	(-0.79)	(-1.58)	(-0.20)			
3	-0.56*	-0.31	-0.25	0.59	0.79	0.04
	(-1.99)	(-1.72)	(-0.99)			
4	-0.65*	-0.37**	-0.28	0.55	0.77	0.09
	(-1.87)	(-2.08)	(-0.85)			
Big	-0.59**	-0.43**	-0.28	0.68	0.76	0.14
	(-2.49)	(-2.80)	(-1.31)			
Small-Big	1.96***	0.83***	1.13**	0.07	0.20	0.05
	(3.00)	(3.00)	(2.00)			

*** Significant at or above the 0.01 level
** Significant at the 0.05 level
* Significant at the 0.10 level

book-to-market equity can be easily realized: first, the size figure of distressed portfolio and non-distressed portfolio in each size quintile is not very different from each other, indicating that distressed firms and their non-distressed counterparts have rather close average market capitalization; second, unlike that distressed firms and the non-distressed firms are similar in size, the book-to-market equity of distressed firms is higher on average than the equivalent non-distressed firms, as shown under the label "Average B/M". Given the common recognition of firm size and book-to-market equity as proxies for some unknown systematic risk factor (Fama and French, 1993), the above findings suggest that in the context of the sensitivity of the two types of portfolios to an other than market risk factor, distressed portfolios do not appear to be less risky than the equivalent non-distressed portfolios. Furthermore, the sensitivity of the two types of portfolios to the market risk factor is considered separately, which is presented as portfolio beta under the label "Average Beta". The uniformly higher betas obtained for distressed portfolios indicate that the distressed portfolios are perceived to be riskier than the non-distressed ones. In a word, the statistics obtained on size and book-to-market factors together with the estimated portfolio betas all suggest that, under an efficient market circumstance, no matter in which size quintile, a distressed portfolio is expected to outperform the equivalent non-distressed portfolio due to the higher systematic risk it bears. Therefore, these statistics have automatically eliminated the traditional risk-return-based explanation for an underperformance that would be observed from any of the five distressed portfolios comparing with the stock return on the equivalent non-distressed portfolio.

Before moving on to discussing about portfolios' stock returns after portfolio formation, the prior-year monthly returns on the ten portfolios are also worth paying some attention to. According to Beaver's (1968) investigation, firms underpeform the market for up to four years before eventually go bankruptcy. If that is the case, even though due to resource limitation it is not possible to clearly identify any bankrupt firms in this study, nor the exact time when firms actually claimed for bankruptcy (z-score only can determine if a firm is likely to be at bankruptcy risk), it is still quite reasonable to attribute the lower returns to market underreaction to distress risk when lower prior-year monthly returns are observed on distressed portfolios. Agarwal and Taffler (2008) provided some results which confirm the underperforming behavior of distressed firms. They showed that the monthly prior-year return on distressed portfolio is lower than the return on the non-distressed portfolio in three out of five size quintiles, and the biggest prior-year return difference appeared in the smallest size quintile (1.04%). The average monthly prior-year return on each two-way sorted portfolio is presented under the corresponding label in Panel A. Interestingly as it shows in the table, the situation is quite in contrast with what was suggested in Agarwal and Taffler's (2008) paper: instead of showing lower monthly prior-year return, distressed portfolio outperforms the equivalent non-distressed portfolio in three out of five size quintiles with a particularly big lead in the smallest size group (2.18% for distressed firms and 1.42% for non-distressed firms). Therefore, Agarwal and Taffler (2008) claimed the lower monthly prior-year return on small distressed firms as evidence confirming market underreaction hypothesis, but obviously the similar kind of evidence is not obtained based on the sample of this study.

Our main interest in Table IV is to compare the excess stock returns on distressed and non-distressed portfolios during the subsequent year after portfolio formation. Agarwal and Taffler (2008) found that holding the two-way sorted portfolios for 12 months after formation, either the average excess monthly stock return on distressed portfolio is significantly lower than the excess return on non-distressed portfolio in the same size quintile, or the difference between the two portfolios is not significantly different from zero. On the other hand, they also found that the size effect appears to be strong in both distressed (0.77% per month, t = 2.27) and non-distressed (0.99% per month, t = 3.74) portfolios. Based on the two findings, Agarwal and Taffler (2008) were not able to reject either null Hypothesis $H1_0$ or $H2_0$, therefore conclude that size effect cannot proxy for distress risk.

Following Agarwal and Taffler's (2008) methodology, the average monthly excess return is computed by taking the time-series average of the difference between monthly stock returns and the one-month Treasury bill rate observed at the beginning of the month, and presented under the label "Average Monthly Excess Return" in Panel A. The figures together with their corresponding t-test results show that there are seven out of the ten portfolios earning returns significantly higher than the one-month T-bill rate, and the all three remaining portfolios appear to be the distressed portfolios with bigger size. If financial distress risk is systematic risk as believed by Chan and Chen (1991) and Fama and French (1992) among others, a puzzle directly arises at this point with respect to the implied risk-return relationship: based on the belief, firms with distress risk should earn higher return to compensate the higher embedded risk, but here in contrast, while the average monthly excess returns on the equivalent non-distressed portfolio show to be significant positive, that on the three distressed portfolios are found, statistically speaking, no higher than one-month T-bill rate. Obviously, the estimated return figures together have made it difficult to prove within the range of the samples of this study that distress risk embedded in firms has taken the expected effect on those firms' stock return. At the same time, the no statistically significant excess returns on three distressed portfolios have signaled a trouble in rejecting null Hypothesis $H1_0$ which predicts for no outperformance of distressed portfolio over non-distressed portfolio after controlling for size factor.

In order to make the comparison of the average monthly excess returns on distressed portfolios and non-distressed portfolios more straightforward for testing on null Hypothesis $H1_0$, five arbitrage portfolios are further formed on the base of the two-way-sorted portfolios. Specifically, an arbitrage portfolio is constructed by longing on a distressed portfolio and at the same time shorting on the non-distressed portfolio in the same size quintile. Following the same way as used to estimate the return on the ten portfolios, the returns on the five arbitrage portfolios are calculated as monthly average and presented in the last column in Panel A, which is labeled "Difference". As noted in the column, despite that all the return estimates, except for one, are positive, none of them has high enough *t*-test result to determine that the average portfolio return is significantly different from zero. Although it does not show that any of the arbitrage portfolios has earned any significantly negative returns as they did based on Agarwal and Taffler's (2008) sample collection, the insignificant return results (return difference between distressed and non-distressed portfolios) still finds consistent with the prediction of null Hypothesis $H1_0$ that distressed stocks will not anymore earn higher returns than non-distressed stocks after controlling for size. Therefore, on this basis, we are not able to reject null Hypothesis $H1_0$.

To test null Hypothesis $H2_0$, size effect is next examined on the distress-risk-factor-controlled basis. In order to do that, two other arbitrage portfolios, one on the distressed side and another on the non-distressed side, are formed based on size – long on firm stocks in the smallest size quintile and short on firm stocks in the largest size quintile. The average monthly return figures of the two arbitrage portfolios are presented in the bottom row labeled "Small-Big". As shown in the place, the size-based trading strategy has gained positive return on both arbitrage portfolios, and moreover, the two positive returns are significant at the 0.01 level (for distressed group: 1.62% per month, t = 3.14; for non-distressed group: 1.05% per month, t = 3.52). The significant higher than zero returns on the two arbitrage portfolios is a confirmation of the existence of strong size effect among our sample firms regardless whether they are at distress risk or in a good financial healthy condition. Therefore, the estimated results based on the sample of this study cannot provide a valid basis to reject null Hypothesis $H2_0$ which predicts that after distress risk factor is taken control size effect will still exist among firms regardless their financial health status. Moreover, it is also worth noting that although strong size effect appears among sample firms on both distressed and non-distressed sides, the difference of the returns on the two size-based arbitrage portfolios is not found significantly different from zero (t = 1.47). Therefore, on this basis, once again we are not able to find evidence to reject null Hypothesis $H1_0$.

The investigation on the relationship between distress risk and size effect has so far been only taken on the portfolio's raw return basis. Obviously, our failure in rejecting both null Hypothesis $H1_0$ and $H2_0$ has brought us a problem to accept the distress risk explanation for size effect. However, as a portfolio's raw return is an integrated consequence of the impacts of different risk resources rather than any single risk factor alone, in order to be able to examine the effect of a specific risk factor, i.e. distress risk, on portfolio return, Fama and French (1993) three-factor regression model is employed next to get other risk factors into a proper control. The model is run on each of the ten two-way sorted different portfolios as well as the arbitrage portfolios. The main focus of this regression analysis is on the estimated intercept (β_1) and its statistical significance as they would tell us whether a portfolio of interest earns superior return on a common known risk-adjusted basis.

The first two columns in Panel B of Table IV presents the intercepts (β_1), i.e. risk-adjusted returns, obtained from the Fama and French (1993) three-factor regression analysis separately conducted on each of the ten two-way-sorted portfolios. Based on the results exhibited in the table, Fama and French (1993) three-factor regression model seems to have a problem in explaining the returns on some of the portfolios as there are seven out of ten estimated intercepts found to be statistically significant at or above the 0.10 level. Under the assumption that all the systematic risks are captured by the market, size and book-to-market factors in the regression model, the intercept β_1 is an explicit interpretation of the deviation of a portfolio's actual return from the expected return on that portfolio on the risk-return basis. A positive intercept is an indication of a portfolio's outperformance while an intercept with negative sign signals for an underperformance of a portfolio on the other hand.

As shown in the Panel B, among the seven intercepts obtained with statistical significance, five of them have a negative sign in front (except for the two portfolios in the smallest size quintile), suggesting that those five portfolios actually have earned lower than expected returns, given the risk level they were bearing at the time. It is worth drawing an attention particularly on the estimated β_1 on the distressed portfolios in the 3rd, 4th and 5th size quintile. The β_1 obtained for the three portfolios are -0.56%, -0.65% and -0.59%, respectively. Recalling from Panel A that, a puzzle was earlier arisen from this three distressed portfolios because their excess returns were found insignificantly different from the one-month T-bill rate. With the negative risk-adjusted returns on the three portfolios shown in Panel B, it is much clearer now that the extremely low returns earned by those three portfolios were not because that the risk level of the three portfolios was comparable to that of T-bill, but to large extent due to the three portfolios' lower than expected performance. Furthermore, when the negative risk-adjusted returns on the same three portfolios are compared with the equivalent non-distressed portfolios, the results presented in the table tell us that, although the risk-adjusted returns on the three non-distressed portfolios in the 3rd, 4th and 5th size quintile are shown to be negative, that is -0.31%, -0.37% and -0.43%, respectively, the first estimate is determined to be statistically insignificant (t = 1.72), and the magnitude of the other two significantly negative risk-adjusted returns are also smaller than that of the return results shown on the corresponding distressed portfolios. Therefore, the comparison of the risk-adjusted return on the portfolios cannot provide us any evidence of non-distressed portfolios being outperformed by the equivalent distressed portfolios.

Besides the five negative β_1 s, the other two β_1 s are determined to be positive, which are the estimated risk-adjusted stock returns earned by the distressed and non-distressed portfolio in the smallest size quintile (β_1 = 1.37%, t = 2.18 for distressed portfolio; β_1 = 0.54%, t = 2.16 for the equivalent non-distressed portfolio). Despite that these two results has explicitly suggested the existence of size effect, what is interesting, especially when compared to the results reported by Agarwal and Taffler (2008), is that the estimated risk-adjusted return on the distressed portfolio is shown much higher than that earned by the non-distressed side portfolio.[28] Since in Agarwal and Taffler's (2008) study, the positive risk-adjusted return is determined to be statistically significant only on the non-distressed side but not on the distressed side, they had no problem to exclude distress risk explanation but attribute the superior return found on the smallest non-distressed portfolio purely to size effect. But with the estimated result based on the sample of this study, the explanation for the much higher return on the smallest distressed portfolio is mixed. On one hand, the old explanation may still stand. Although both portfolios are assigned to the smallest size quintile, the descriptive statistics in Panel A has already shown us non-negligible size difference also exists between the two portfolios: the average market capitalization of the smallest distressed portfolio is \$65.80 million and \$80.76 million for the equivalent non-distressed portfolio. Therefore, it is possible that the higher return on the distressed side is just another confirmation of size effect. Furthermore, even if the size factor is presumably taken control by *SML* in the three-factor model, the weak fitness of the regression model stated by the relatively low R^2 (0.20) also hinds that the size effect might not have been well captured as expected, which results the difference in estimated β_1 of the two portfolios. On the other hand, irrespective to the average size difference realized between the distressed and non-distressed portfolios in the smallest size quintile, the distress risk is the major factor that distinguishes the two portfolios. According to the descriptive statistics exhibited in Table II, distressed firms are highly concentrated in the distressed portfolio in the smallest size quintile.[29] If the estimated higher risk-adjusted return on the distressed portfolio along with its statistical significance is as result of the sufficient sample size given, distress risk factor should not be completely excluded as another plausible explanation for the higher risk-adjusted return examined on the distressed side, and so is its connection to size effect. However, having acknowledged that either the size or

[28] Agarwal and Taffler's (2008) also reported some similar findings based on their UK samples: the estimated β_1 is 0.23% and 0.79 for the distressed portfolio and the non-distressed portfolio in the smallest size quintile, respectively. But the positive risk-adjusted return is determined to be statistically significant only on the non-distressed side % (t = 5.90) but not on the distressed side (t = 1.19).

[29] Given the same number of firms assigned to each size quintile, 20.83% of the firms in the smallest quintile have z-score smaller than 1.81, suggesting that they are determined to be financially distressed.

the distress risk could have affected the smallest distressed portfolio's return, the presumed specific positive impact resulted from distress risk on that portfolio return is soon denied due to the lack of statistical significance of the return difference between of the two portfolios, which will be discussed in more detail next.

A simple comparison of risk-adjusted return between distressed and non-distressed portfolio alone is not sufficient to determine a rejection or an acceptance of null hypothesis $H1_0$. To do that, the statistical significance of the return difference has to be also taken into account. Therefore, following the same way of estimating a portfolio's risk-adjusted return, the return on each arbitrage portfolio, which is formed by longing on distressed portfolio and shorting on non-distressed portfolio in each size quintile, is again regressed on the Fama and French's (1993) three factors; and the estimated intercept β_1s along with their *t*-test results are presented in the column labeled "Difference" in Panel B of Table IV. As shown in the column, irrespective to the result obtained for the Small-Big arbitrage portfolio (presented in the last row), the estimated β_1s are uniformly negative except for that in the small size quintile, suggesting that after controlling for risk, the return on the distress-risk-based portfolio is negative. Another way to look at the return on the arbitrage portfolio is that it is the return difference between distressed and non-distressed portfolio. Since the long position is taken by distressed portfolio in this arbitrage trading strategy, the negative β_1 obtained also implies that a financially distressed portfolio tends to earn lower return than that earned non-distressed portfolio on the risk-adjusted basis. Therefore, as the results have turned out to be the way as predicted by null Hypothesis $H1_0$, we are unable to reject this null hypothesis.[30] Taking the statistic significance of the results into consideration would not make any difference towards whether to reject or accept null Hypothesis $H1_0$, because the low *t*-test results of the estimated β_1s obtained for the arbitrage portfolios simply suggested that the actual risk-adjusted returns on these portfolios would not be significantly different from

[30] Because of the extremely low fitness of the regression model implied by the R^2 (0.05), although the risk-adjusted return of 1.13% (t = 2.00) for the Small-Big arbitrage portfolio is an exception among all results shown in the "Difference" column, the positive and statistically significant β_1 cannot be considered as a firm evidence for a rejection to null Hypothesis $H1_0$. Also due to too much noises assumed in the regression analysis on this specific group of samples, no further discussion is addressed on this estimated β_1.

zero no matter whether the estimates obtained are positive or negative in number.[31] Moreover, as to the explanation of superior returns found on the smallest distressed portfolio which has been discussed earlier, although the small size and the financially-distressed characteristic possessed by that portfolio were considered as the two competing underlying explanations to the portfolio's superior return, the insignificant risk-adjusted return (β_1 = 0.85%, t = 1.57) shown for the arbitrage portfolio in the smallest size quintile suggests that the distressed portfolio does not earn higher return over the equivalent non-distressed portfolio. Therefore on this basis, the superior return found on the smallest distressed portfolio should be attributed to the portfolio's small size rather than the specific distress character it possesses. In addition, based on this insignificant estimate of the risk-adjusted return on the smallest-sized arbitrage portfolio, we are also unable to reject null Hypothesis $H1_0$, which predicts no outperformance of distressed firms over financially healthy firms.

The null Hypothesis $H2_0$ is also tested on risk-adjusted basis through the examination on the estimated intercepts obtained from the Fama and French's (1993) three-factor regression on the two size-based arbitrage portfolios. The estimated β_1, i.e. the risk-adjusted return on the arbitrage portfolio, is 19.96% per month (t = 3.00) and 0.83% per month (t = 3.00) for the arbitrage portfolio on the distressed side and the non-distressed side, respectively. If the relationship between size effect and distress risk as suggested by Chan and Chen's (1991) and Fama and French's (1992) financial distress factor hypothesis exists, the size effect would vanish once distress risk factor is taken control. But obviously, this prediction is not approved by the estimated β_1 as both results are shown to be positive and significantly different from zero at the 0.01 level, suggesting a consistent outperformance of small-sized firm over bigger-sized firm on both distressed and non-distressed sides. Based the statistically significant and positive β_1 s obtained for the two arbitrage portfolios, we are not able to reject null Hypothesis $H2_0$ on the risk-adjusted basis.

[31] Considering the rather imbalanced sample size of distressed firms and non-distressed firms (on average, only 9.6% of sample firms in each year are classified as being financially distressed by Altman's Z-Score), the insignificance of the negativity of obtained intercept results is likely due to large standard error resulted from the relatively small sample size of distressed firms.

Following is a brief summary of the main findings from the analysis done above. After forming ten portfolios based on two-way sorts on size and Altman's (1968) z-score, the return difference between distressed and non-distressed portfolios is examined through a further formation of arbitrage portfolio. It is found that none of the five formed arbitrage portfolios has produced profit significantly different from zero based on the underlying trading strategy, suggesting that a distressed portfolio is not able to outperform a non-distressed portfolio, given that both portfolios are from the same size quintile. On this basis, therefore, null Hypothesis $H1_0$ cannot be rejected. That is, after controlling for size factor, a distressed stock does not earn return any higher than that earned by a non-distressed stock. The same conclusion can also be drawn on the risk-adjusted basis. On the other hand, the finding with respect to size effect does not reconcile with what is implied by the financial distress factor hypothesis, because even if distressed portfolios and non-distress portfolios are investigated separately, within each group smaller-sized portfolio's outperformance over larger-sized portfolio is still found strongly consistent – the size effect does not vanish after distress risk has been taken in control. As a result, we are unable to bring any convincing evidence to reject null Hypothesis $H2_0$ either. Failing to reject both null Hypothesis $H1_0$ and $H2_0$ automatically overruled the distress risk explanation for size effect as proposed by Chan and Chen (1991) and Fama and French (1992) in their financial distress factor hypothesis. As a matter of fact, based on the sample of this study, the market does not seem to compensate a firm with a higher stock return for higher financial distress risk that firm bears. Moreover, although a tendency of financially distressed firm to earn lower than expected return is hinted by the negative intercepts obtained through regression analysis, the low statistical significance along with those results suggest that the actually risk-adjusted return difference between distressed and non-distressed portfolio is not different from zero. Therefore, on this basis, the rightness of the market underreaction hypothesis proposed by Dichev's (1998) and Campbell, Hilscher, and Szilagyi's (2006) etc. could neither be firmly confirmed.

According to the financial distress factor hypothesis, book-to-market effect (value effect) is also believed to be linked with financial distress risk: the higher return observed on value firms, i.e. firms with high book-to-market ratio, can be attributed to those firms being relatively distressed. To test the relationship between distress risk and book-to-market effect, the same empirical analysis is carried out on the ten portfolios formed on two-way sorts on book-to-market and

Altman's (1968) z-score. Summary statistics are provided in Panel A of Table V first, which is followed by Fama and French (1993) three-factor regression analysis results reported in Panel B in the same table.

The average market capitalization is demonstrated for each the ten two-way sorted portfolios in Panel A of Table V. Comparing them with the figures reported in Agarwal and Taffler's (2008) paper, it obviously shows that American firms are much larger than UK firms on average. A further attention needs to be drawn on the portfolio's average market capitalization presented in Panel A, because, as shown in the table, the average market capitalization presented for distressed portfolio in each book-to-market quintile is larger than that of the equivalent non-distressed portfolio with the only exception in the 2nd book-to-market quintile, which is quite contrary with Agarwal and Taffler's (2008) finding. The larger statistics found on the distressed side is also in conflict with the positive correlation of size factor and Altman's (1968) z-score (0.062) reported in the Table III. The conflicting result may concern the sample size of distressed firms. In Panel B of Table II it is shown that among the entire sample collection there are only a limited number of sample observations of distressed firm in each B/M quintile. Therefore, it is reasonable to believe that the limited sample size of distressed firm has caused a deviation of the estimated figure from the true average market capitalization of distressed portfolio. Regarding the average book-to- market ratio, overall speaking, the estimated average for the distressed and non-distressed portfolio in a same B/M quintile is very close to each other except for the highest B/M quintile where a relatively higher ratio is realized on the distressed side. As for the average beta estimated for the ten portfolios on the other hand, it is shown that the portfolios on the distressed side uniformly have higher beta than the equivalent portfolios on the non-distressed side. Overall speaking, none of the distressed portfolios is perceived to be less risky than the corresponding non-distressed portfolios. Last but not the least, in a preliminary investigation conducted to examine whether the value effect exists on the entire-sample basis, the outperformance of firm with high book-to-market ratio over low book-to-market firm has determined to be rather strong.[32] But interestingly, it is shown in the table that firm's book-to-market ratio and prior-year

[32] The highest book-to-market equity firms are found outperform the lowest book-to-market equity firms with 0.49% per month on average at the 0.05 significance level (*t* =2.12). The process of investigating the book-to-market effect on the entire sample basis is not reported in this paper, as it is not the focus of the study, but a summary report in Excel is available upon request.

Table V

B/M and Distress Risk in Stock Returns

Portfolios are formed as follows: at the end of June of each year from 1989 to 2008, all the stocks in the sample are allocated to two groups based on whether their latest available z-score is smaller or larger than 1.81. The stocks are also independently ranked on B/E and grouped into five portfolios. Ten portfolios are then formed at the intersections of B/M and z-score. For each B/M quintile, an arbitrage portfolio labeled "Difference," long on distressed stocks and short on non-distressed stocks, is also formed. Panel A presents the portfolio summary statistics. B/M is computed as the ratio of book value of equity (excluding preference capital) plus deferred taxes less minority interests from the latest available accounts divided by the market value of equity on June 30. Average monthly excess return is the time-series average of difference between monthly stock returns and the one-month Treasury bill rate observed at the beginning of the month. Portfolio betas are the sum of slopes in the regression of the return on a portfolio on the current, prior, and next month's market returns. Average size, average B/M, and average momentum are the time-series averages of monthly averages of market capitalization, B/M, and prior 11-month returns (excluding June), respectively, for stocks in the portfolio at the end of June of each year. Panel B presents the intercepts and adjusted R^2 for each of the portfolios from the following Fama and French (1993) three-factor model (Equation 2):

$$R_{it} - R_{Ft} = \beta_1 + \beta_2 (R_{Mt} - R_{Ft}) + \beta_3 SMB_t + \beta_4 HML_t \varepsilon_{it}$$

where R_{it} is the equally weighted return on portfolio i during month t, R_{Ft} is the one-month Treasury bill rate at the beginning of month t, and R_{Mt} is the value-weighted return during month t. Here SMB_t is the return on the mimicking portfolio for the size factor during month t, and HML_t is the return on the mimicking portfolio for the B/M factor during month t. Also, ε_{it} is a mean-zero stochastic error term. Data for variables R_{Mt}, SMB_t and HML_t are all taken from taken from Professor Kenneth R. French's website. Figures in parentheses are the t – statistics.

Panel A. Summary Statistics

B/E	Average Market Cap ($m)		Average B/M		Average Monthly Prior-Year Return (%)		Average Beta		Average Excess Monthly Returns (5)		Difference
	z<1.81	z>1.81	z<1.81	z>1.81	z<1.81	z>1.81	z<1.81	z>1.81	z<1.81	z>1.81	
Low	11366.39	9938.15	0.07	0.06	2.86	2.18	1.19	0.94	1.39***	0.69***	0.68
									(3.33)	(3.22)	(1.60)
2	8549.65	8830.01	0.21	0.23	2.22	2.17	1.11	0.73	1.12***	0.64**	0.48
									(3.33)	(2.73)	(1.67)
3	5407.10	4156.76	0.39	0.40	2.07	1.44	0.98	0.90	0.52*	0.81*	-0.15
									(1.97)	(1.78)	(-0.43)
4	3594.14	1766.55	0.61	0.60	1.59	0.98	1.19	0.99	0.28	0.74***	-0.46
									(0.80)	(2.40)	(-1.70)
High	2305.93	676.04	1.25	1.11	0.40	-0.26	1.19	1.05	1.20**	1.20***	-0.01
									(2.48)	(3.58)	(-0.04)
High-Low									-0.20	0.50**	-0.69
									(-0.40)	(2.12)	(-1.63)

Table V

B/M and Distress Risk in Stock Returns (Continued)

Panel B. Fama and French (1993) Regression Results

B/E	Intercept (β_1)			Adjusted R^2		Difference
	z<1.81	z>1.81	Difference	z<1.81	z>1.81	
Low	0.24	-0.19	0.47	0.37	0.79	0.06
	(0.40)	(-1.14)	(0.85)			
2	0.08	-0.17	0.30	0.40	0.78	0.03
	(0.18)	(-1.03)	(0.76)			
3	-0.38**	-0.13	-0.20	0.36	0.79	0.02
	(-2.47)	(-0.29)	(-0.46)			
4	-0.72*	-0.19	-0.53	0.49	0.80	0.01
	(-1.98)	(-1.12)	(-1.46)			
High	0.05	0.12	-0.07	0.50	0.74	0.01
	(0.14)	(0.56)	(-0.19)			
High-Low	-0.18	0.36*	-0.54	0.04	0.25	0.04
	(-0.32)	(1.87)	(-0.94)			

*** Significant at or above the 0.01 level
** Significant at the 0.05 level
* Significant at the 0.10 level

return are monotonically inversely related, suggesting that firms with high book-to-market ratio usually are the losers in the market during the prior year until their fiscal year-end reports become publicly available. With the confirmation of the existence of book-to-market anomaly among our samples, the next step is to find out if the change of the role of firms with high book-to-market equity from market loser to market winner has anything to do with distress risk, i.e. if distress risk is the driving force behind the market anomaly value effect.

To test null Hypothesis $H1_0$ in the context of examining the relationship between effect and distress risk, our focus is on the return difference between distressed and non-distressed portfolio after controlling book-to-market factor. Under the mentioned circumstances, null Hypothesis $H1_0$ predicts that distressed portfolio will not earn higher return over the equivalent non-distressed portfolio. When the test was run by Agarwal and Taffler (2008), they only found the average return, which is equal to the return difference of the two portfolios, on the constructed arbitrage portfolio (long on distressed stocks and short on non-distressed stocks) either negative or statistically insignificant; and as a consequence, they were forced to accept the null hypothesis. Following Agarwal and Taffler's (2008) methodology, the average return is calculated separately after five arbitrage portfolios have been constructed, and the estimated results are reported in the column labeled "Difference" in Panel A of Table V. Irrespective to the positive or negative sign of the obtained average return estimates, none of them has attained high enough statistical significance to suggest that a difference between distressed and non-distressed portfolio really exists. The insignificant return results obtained on the arbitrage portfolios also automatically make the null Hypothesis $H1_0$ acceptable rather than being rejected.

For the purpose of testing value effect on both distressed and non-distressed side separately, two other zero-cost portfolios are constructed based on portfolio's book-to-market ratio, and the portfolio return on each side is obtained by subtracting the return on the lowest book-to-market portfolio from the return on portfolio with the highest book-to-market equity. Between the two average return estimates presented in the row labeled "High-Low", the return on the non-distressed side is determined to be positive (0.50% per month) and statistically significant at the 0.05 level (t = 2.12), suggesting that value effect still exists in one of the portfolios from which the impact of distress risk has been eliminated. Therefore, on this basis, we are not able to reject null Hypothesis $H2_0$.

All the intercepts obtained from the Fama and French (1993) three-factor regression analysis are presented in Panel B of Table V. The ten two-way sorted portfolios' performances are examined first, and the estimated risk-adjusted return on each portfolio is presented in the second and third column in Panel B of Table V. The standard model seems to have a problem in explaining the returns on the two distressed portfolios in the 3rd and 4th B/M quintile, because the intercepts obtained for the two distressed are both estimated to be negative and statistically significant above the 0.10 level (-0.38% per month, t = -2.47; -0.72% per month, t = -1.98, respectively). The negative intercepts obtained suggest that the realized returns on the two distressed portfolios are lower than the market expectations providing that the risk indicated/represented by the three Fama and French (1993) three factors are taken into account when pricing the assets. The intercepts presented in the column labeled "Difference" in Panel B are the estimated risk-adjusted return on all distress-risk-based arbitrage portfolios of which the raw returns have been examined in Panel A. In the similar investigation done by Agarwal and Taffler (2008), they found four out of six estimated intercepts significantly negative, and the rest insignificant. The empirical evidence clearly showed that if have had book-to-market factor controlled a distressed portfolio would not earn higher risk-adjusted return than a non-distressed, therefore suggested Agarwal and Taffler (2008) to accept null Hypothesis $H1_0$ also on the risk-adjusted basis. Based on the results presented in Panel B, null Hypothesis $H1_0$ cannot be rejected either because no matter whether the β_1 s obtained are positive or negative in value, none of their t-test results can guarantee that the actual risk-adjusted return on any of the five arbitrage portfolios is significantly different from zero, which is equal to say that none of the distressed portfolios are able to provide higher risk-adjusted return than the equivalent non-distressed portfolios do. Furthermore, the first two intercepts presented in the last row labeled "High-Low" in Panel B are the estimated risk-adjusted returns on the B/M-based arbitrage portfolios. In the investigation of value effect on risk-adjusted basis, although no evidence of value effect is found on the distressed side, the estimated risk-adjusted return of 0.36% per month (t = 1.87) on the zero-cost portfolio on the non-distressed side still suggests that portfolio with the highest book-to-market equity has won over the portfolio with the lowest ratio even after controlling for distress risk factor. On this basis, therefore, we are not able to reject null Hypothesis $H2_0$ also on risk-adjusted basis.

In summary, based on the sample of this study no empirical evidence obtained on raw return or risk-adjusted return basis has enabled us to reject either of the two null hypotheses: after controlling for book-to-market factor, distressed portfolios are not able to bring investors higher returns over the equivalent non-distressed portfolios as a result of the extra risk loaded on them; On the other hand, even if distress risk factor has been taken in control, value effect is still proved to be significantly strong on the non-distressed side. Therefore, with respect to the relationship between effect and distress risk, the empirical-based results have led us to a same conclusion as which was drawn by Agarwal and Taffler's (2008) That is, higher returns on firms with high book-to-market equity are not closely related to the distress risk embedded in those firms as suggested in Chan and Chen's (1991) and Fama and French's (1992) financial distress factor hypothesis. However, although the intercept from the Fama and French (1993) three-factor regression analysis is determined to be negative in value for three B/M based arbitrage portfolios, the three estimated negative risk-adjusted return is not statistically significant enough to provide a support to a market underreaction story which was suggested by Agarwal and Taffler's (2008) empirical results.

6.2.2. Test on the Link between Momentum Effect and Distress Risk

The medium-term continuation of stock returns (momentum effect) has been widely observed in the worldwide financial market. Several previous studies have been contributed to this field by scholars who were attempting to find the true cause(s) of this the most challenging market anomaly among others (e.g.: Ang, Chen and Xing, 2001; Moskowitz and Grinblatt 1991, Bulkley and Nawosah 2008). Agarwal and Taffler (2008) proposed a new theory which suggests that a connection between momentum effect and distress risk. In their opinion, and the existence of the phenomenon is to large extent due to a market underreaction to the distress risk.

Agarwal and Taffler's (2008) speculation on the existence of the link between the momentum effect and financial distress risk was built up on two bases. The first basis is the evidence of distress stock's underperformance which has not only been reported in many previous studies (Beaver, 1968; Dichev, 1998; Campbell, Hilscher, and Szilagyi, 2006), but also has been found by the two authors themselves. The second basis is Avramov, Chorida, Jostova and Philipov's (2007a) finding of the connection between momentum and credit risk.[33] Therefore, in order to find out whether Agarwal and Taffler's (2008) new theory also applies to U.S. market, investigation needs to be conducted in two aspects: if distressed firms are constantly outperformed by non-distressed firms for a period of time; and if the otherwise absent medium-term continuation phenomenon appears among distressed firms. The following two null hypotheses which were originally set up in Agarwal and Taffler's (2008) study are to be retested on the samples of this study next:

- $H3_0$: Distressed firms do not underperform non-distressed firms.

- $H4_0$: Medium-continuation of returns appears in both distressed stocks and non-distressed stocks.

If Agarwal and Taffler's (2008) theory is pervasively acceptable, then we will expect to find some empirical evidence which will enable us to reject the two null hypotheses.

Panel A of Table VI summarizes the statistics of the ten portfolios formed on two-way sorts on prior-year return and Altman's (1968) z-score. It is worth noting that, all the five distressed portfolios have higher average book-to-market equity and beta than the equivalent non-distressed portfolios, therefore suggesting that the sensitivity of distressed portfolio's return to systematic risks is none less sensitive than that of non-distressed portfolios. In addition to the estimated monthly raw returns on the ten two-way sorted portfolios, Panel A also presents the estimated monthly raw returns on various arbitrage portfolios which are formed based on either distress risk factor or portfolio's prior-year performance obeying the same formation rule employed before.

[33] However, while Agarwal and Taffler (2008) considered credit risk and financial distress risk as two synonymous concepts, Avramov, Chorida, Jostova and Philipov (2007a) mentioned in their study that credit rating is not necessarily a good proxy for distress risk.

Correspondingly, all portfolios' the risk-adjusted return estimates obained from the Fama and French (1993) three-factor regression analysis are reported in the Panel B of the same table.

To reject null Hypothesis $H3_0$, the emphasis is put on finding concrete evidence to prove that on average a distressed firm would be outperformed by a non-distressed portfolio but not another way around – showing no significant return difference when comparing the return on the two types of portfolio would not be good enough. Therefore, in addition to a requirement of a negative sign appearing in front of the estimated return on a distress-risk-based arbitrage portfolio, the *t*-test result coming along with that return estimate is also a matter of particular importance in this test in terms of determining whether a distressed portfolio earns significantly lower return than it would earn if it is in a financially healthy condition. But unfortunately, as reported in the column labeled "Difference" in Panel A, no matter whether the obtained estimate shows to be positive or negative, none of the *t*-test result in the parenthesis below the obtained estimates could pronounce the actual monthly average return difference between a distressed and the equivalent non-distressed portfolio to be significantly different from zero. Furthermore, statistically significant return difference between the two portfolios can neither be found on risk-adjusted basis (see Panel B). As a result, null Hypothesis $H3_0$ ought to be accepted. No evidence of distressed portfolio's underperformance has been found based on the sample of this study.

On the other hand, the investigation on the monthly returns on the two momentum-based portfolios (Winner-Loser portfolio) seems to provide some evidence to reject null Hypothesis $H4_0$. The raw returns on the two momentum-based portfolios presented in Panel A are -0.13% per month (t = 0.22) and 0.07% per month (t = 0.27), respectively. Irrespective to their values, both of the estimates are insignificantly different from zero, suggesting that momentum effect is neither found among distressed firm samples nor among non-distressed firm samples, which is just opposite to the result predicted by null Hypothesis $H4_0$. Furthermore, when the same portfolios' monthly returns are examined on risk-adjusted basis, momentum effect is found among non-distressed firm samples only (0.36% per month, t = 1.87); but both the value and the *t*-test result of the intercept obtained on the distressed side indicate that momentum effect is absent from distressed firm samples (-0.18% per month, t = -0.32). As a result, null Hypothesis $H4_0$ has to be rejected on risk-adjusted basis as well. The conclusion regarding the link between

Table VI

Prior-Year Return and Distress Risk in Stock Returns

Portfolios are formed as follows: at the end of June of each year from 1989 to 2008, all the stocks in the sample are allocated to two groups based on whether their latest available z-score is smaller or larger than 1.81. The stocks are also independently ranked on prior-year returns and grouped into five portfolios. Ten portfolios are then formed at the intersections of prior-year returns and z-score. For each prior-year return quintile, an arbitrage portfolio labeled "Difference," long on distressed stocks and short on non-distressed stocks, is also formed. Panel A presents the portfolio summary statistics. B/M is computed as the ratio of book value of equity (excluding preference capital) plus deferred taxes less minority interests from the latest available accounts divided by the market value of equity on June 30. Average monthly excess return is the time-series average of difference between monthly stock returns and the one-month Treasury bill rate observed at the beginning of the month. Portfolio betas are the sum of slopes in the regression of the return on a portfolio on the current, prior, and next month's market returns. Average size, average B/M, and average momentum are the time-series averages of monthly averages of market capitalization, B/M, and prior 11-month returns (excluding June), respectively, for stocks in the portfolio at the end of June of each year. Panel B presents the intercepts and adjusted R2 for each of the portfolios from the following Fama and French (1993) three-factor model (Equation 2):

$$R_{it} - R_{Ft} = \beta_1 + \beta_2 (R_{Mt} - R_{Ft}) + \beta_3 SMB_t + \beta_4 HML_t \varepsilon_{it}$$

where R_{it} is the equally weighted return on portfolio *i* during month t, RFt is the one-month Treasury bill rate at the beginning of month *t*, and RM_t is the value-weighted return during month *t*. Here SMB_t is the return on the mimicking portfolio for the size factor during month *t*, and HML_t is the return on the mimicking portfolio for the B/M factor during month *t*. Also, ε_{it} is a mean-zero stochastic error term. Data for variables R_{Mt}, SMB_t and HML_t are all taken from taken from Professor Kenneth R. French's website. Figures in parentheses are the *t-statistics*.

Panel A. Summary Statistics

Prior-Year Return	Average Market Cap ($m)		Average B/M		Average Monthly Prior-Year Return (%)		Average Beta		Average Excess Monthly Returns (5)		Difference
	z<1.81	z>1.81	z<1.81	z>1.81	z<1.81	z>1.81	z<1.81	z>1.81	z<1.81	z>1.81	
Loser	2301.99	3252.57	0.87	0.67	-2.15	-1.90	1.37	1.04	1.30**	1.07***	0.23
									(2.54)	(4.13)	(0.55)
2	9054.67	5121.08	0.70	0.52	0.21	-0.08	1.46	1.14	0.77**	0.65**	0.12
									(2.44)	(2.50)	(0.38)
3	10663.59	5933.17	0.59	0.44	1.14	0.98	1.63	1.22	0.56	0.61**	-0.05
									(1.58)	(2.17)	(-0.23)
4	22554.52	6693.98	0.56	0.38	2.26	2.21	1.11	1.08	0.62	0.72**	-0.10
									(1.72)	(2.65)	(-0.41)
Winner	5666.60	4771.98	0.45	0.32	6.51	5.49	1.36	1.33	1.17**	1.00***	0.18
									(2.41)	(3.46)	(0.50)
Winner-Loser									-0.13	-0.07	-0.06
									(-0.22)	(-0.27)	(-0.11)

Table VI

Prior-Year Return and Distress Risk in Stock Returns (Continued)

Panel B. Fama and French (1993) Regression Results

Prior-Year Return	**Intercept (β_1)**			**Adjusted R^2**		**Difference**
	z<1.81	**z>1.81**	**Difference**	**z<1.81**	**z>1.81**	
Loser	0.24	-0.19	0.47	0.37	0.79	0.06
	(0.40)	(-1.14)	(0.85)			
2	0.08	-0.17	0.30	0.40	0.78	0.03
	(0.18)	(-1.03)	(0.76)			
3	-0.38**	-0.13	-0.20	0.36	0.79	0.02
	(-2.47)	(-0.29)	(-0.46)			
4	-0.72*	-0.19	-0.53	0.49	0.80	0.01
	(-1.98)	(-1.12)	(-1.46)			
Winner	0.05	0.12	-0.07	0.50	0.74	0.01
	(0.14)	(0.56)	(-0.19)			
Winner-Loser	-0.18	0.36*	-0.54	0.04	0.25	0.04
	(-0.32)	(1.87)	(-0.94)			

*** Significant at or above the 0.01 level
** Significant at the 0.05 level
* Significant at the 0.10 level

momentum effect and distress risk has to be made with caution based on the findings though, because as a matter of fact, without obtaining any evidence of momentum effect from the distressed risk side, the rejection to null Hypothesis $H4_0$ alone cannot confirm at all that there is a link between distress risk and a medium-term continuation phenomenon. Agarwal and Taffler's (2008) test on null Hypothesis $H3_0$ and $H4_0$ were based on samples collected from UK market. They found strong evidence against the two null hypotheses. That is first, the distressed loser (the distressed portfolio in the loser quintile) earns significantly lower return than the non-distressed loser; and second, momentum effect exists and only exists among distressed firms. Obviously, the empirical-based analysis on U.S. market just done has not led us to the same conclusion drawn by Agarwal and Taffler (2008). Comparing the portfolio return results obtained with those corresponding results reported in Agarwal and Taffler's (2008) paper, I notice that the biggest inconsistency realized between the two studies is the distressed loser's relative performance in the subsequent year after portfolio formation, despite that the two distressed losers do share the same characteristics.[34] Specifically, when the performance in the subsequent year after portfolio formation is compared between distressed loser and non-distressed loser (non-distressed portfolio in the loser quintile) or between distressed loser and distressed winner (distressed portfolio in the winner quintile), Agarwal and Taffler (2008) clearly showed that in both cases the distressed loser remained as a loser[35], but according to the results provided in Panel A of Table VI, the return difference between the previous loser and the two previous winner has become statistically insignificant (0.23 per month, t = 0.55 and 0.13% per month, t = 0.22, respectively). Agarwal and Taffler (2008) attributed the distressed loser's continuous underperformance to market's underreaction to the distress risk born by firms which have the smallest size and the highest book-to-market equity, as they believed that that type of firms are likely to be the most unpopular and ignorable players in the market, and therefore the most difficult to be valued by the market.

[34] The import characteristics shared by the two distressed losers are as follow: firstly, the portfolio is consisted with firms with the smallest size and the highest book-to-market equity among the entire samples, suggesting that they are likely to be most unpopular and ignorable players in the market; secondly, the average market capitalization, average book-to-market equity and beta of the portfolio together suggest that the portfolio is not less risky than the other two portfolios it is compared with in the analysis i.e. the non-distressed portfolio in the loser quintile and the distressed portfolio in the winner quintile;[34] and thirdly, when comparing its performance with the performance of the non-distressed portfolio in the loser quintile or with the performance of the distressed portfolio in the winner quintile, the portfolio is the prior-year loser in both cases.

[35] The portfolio was outperformed by the equivalent non-distressed loser and the distressed winner with -0.66% per month (t = -3.12) and -0.65% per month (t = -2.17), respectively.

However, based on the results presented in Table VI, even though the distressed loser portfolio in this study consists of the same type of firms, my finding on its performance do not seem to be providing the same ground for a suspicion about market efficiency as provided in Agarwal and Taffler's (2008) study.

6.2.2.1 Statistical Significance Test on Prior-Year Average Monthly Return Difference

Through the investigation on the various portfolios' subsequent performances, I find out that my U.S. market-based results, regarding distressed firm's performance and the question whether the momentum effect is specifically connected with distress risk, are inconsistent with the evidence that have been reported by Agarwal and Taffler (2008). Among others, it is especially surprising that none of the results obtained in this study suggests that a firm would tend to earn lower return if it is financially distressed, even though the opposite evidence have been repeatedly reported in several previous studies which were conducted also based on. As far as this inconsistency in particular is concerned, an important question should be asked up to this point is how reliable are the results obtained based on the sample of this study. The sample distribution provided in Panel C on Table II has already shown that the number of sample observations of distressed firm year is indeed quite small; and in addition to that, there is also a noticeable imbalance between the sample size of distressed firm year and non-distressed firm year. Therefore, on this basis, it is reasonable to suspect that whether the limitations of the sample collection of this study have affected the representativeness of the obtained estimates. In other words, there seems to be a good chance that, due to the small number of sample collections of distressed firm, those results presented in Table VI are just biased estimates which cannot be relied on in terms of representing the market average.

One way to find out how likely that the inconsistency with Agarwal and Taffler's (2008) empirical evidence found in this study regarding the distressed loser portfolio's performance could be due to the impact of this study's limited sample collection of distressed firm year is to expand the investigation to portfolios' prior-year performances, focusing on determining whether significant difference in the prior-year monthly return can be found between the distressed loser portfolio and the non-distressed loser portfolio and also between the distressed loser portfolio and the distressed winner portfolio. Given a satisfactory sample base, the prior-year monthly return on the distressed loser portfolio should be found significantly lower than the same returns on the other two portfolios for the following two reasons: first, even if the market is presumed to be semi-strong efficient, it is reasonable to believe that distressed firms are likely to underperform non-distressed but otherwise equivalent firms before their vulnerable financial status has become public knowledge. Second, for the purpose of testing null Hypothesis $H3_0$ and $H4_0$, all samples are sorted into portfolios in a way that the prior-year return has been settled to be one of the two factors that portfolio formation is based on. Therefore, there should be detectable difference in the prior-year performance between the distressed loser and the distressed winner as implied in their titles.

Table VII provides a brief report of the prior-year average monthly performances of the three concerned portfolios, i.e. the distressed loser, the non-distressed loser and the distressed winner. The return differences between distressed loser and the other two portfolios are first calculated separately for each sample year (presented Column IV and V, respectively), and then on this basis, average return difference and its statistical significance level are determined. As suggested by the two *t*-test results presented in the bottom of Column IV and V, the investigation has failed to show that prior-year average monthly return on the distressed loser portfolio is significantly lower than the return on the non-distressed loser based on the sample of this study (t = -1.27); but on the other hand, the evidence of the distressed loser underperforming the distressed winner during the year prior to portfolio formation date is found significantly strong (t = -16.68).

The two different findings about the distressed loser's prior-year performance compared with the performance of non-distressed loser and distressed winner have given us two different answers to the previously asked question, i.e. whether the inconsistency with the previous empirical evidence found in this study regarding the distressed loser portfolio's performance is resulted because of the limitation of the sample collection of this study. It is much more certain now that the result of the estimated difference in the post-portfolio-formation performances between the distressed loser and the non-distressed loser portfolio (0.23% per month, t = 0.55) is very likely to be biased; and that is probably why I am not able to find evidence to reject the null Hypothesis

Table VII

Portfolio Prior-Year Monthly Return Comparison

Portfolios are formed as follows: at the end of June of each year from 1989 to 2008, all the stocks in the sample are allocated to two groups based on whether their latest available z-score is smaller or larger than 1.81. The stocks are also independently ranked on prior-year returns and grouped into five portfolios. Ten portfolios are then formed at the intersections of prior-year returns and z-score. Column I to Column III present the yearly based average prior-year monthly returns on three portfolios over the sample period. Distressed loser is one of the two portfolios in the lowest prior-year return quintile, which consists of distressed firms. Non-distressed Loser is another portfolio in the lowest prior-year return quintile, which is formed by non-distressed firms. Distressed winner is the portfolio that is constituted by distressed firms which have earned the highest prior-year returns among all sample firms. Column IV presents the prior-year monthly return difference between distressed loser and non-distressed loser (former minus later). Column V presents the prior-year monthly return difference between distressed winner and distressed loser (former minus later). Average prior-year monthly return difference between portfolios, standard error and *t*-test results are provided in the bottom of each respective column.

				Average Prior-Year Monthly Return Difference	
	Column I	Column II	Column III	Column IV	Column V
Year	Distressed Loser	Non-Distressed Loser	Distressed Winner	Loser Quintile Distressed – Non-Distressed	Distressed Loser – Winner
2008	-5.39	-3.29	3.61	-2.11	-9.01
2007	-2.18	-1.01	7.93	-1.17	-10.11
2006	-2.40	-1.88	7.30	-0.51	-9.69
2005	-3.07	-2.03	4.62	-1.05	-7.70
2004	0.26	-0.18	10.08	0.43	-9.82
2003	-1.68	-2.44	8.55	0.76	-10.23
2002	-2.64	-2.50	9.13	-0.13	-11.76
2001	-0.89	-1.78	6.38	0.89	-7.27
2000	-4.54	-5.08	7.28	0.54	-11.83
1999	-4.46	-2.71	5.84	-1.75	-10.30
1998	-1.84	-1.67	6.27	-0.18	-8.11
1997	-0.96	-0.95	5.66	-0.02	-6.62
1996	-1.11	-1.11	7.63	0.00	-8.75
1995	-0.07	-1.05	5.09	0.98	-5.16
1994	-1.51	-1.48	2.86	-0.03	-4.37
1993	-0.53	-1.09	5.88	0.55	-6.42
1992	-1.91	-1.65	10.25	-0.26	-12.16
1991	-2.41	-1.62	6.94	-0.79	-9.35
1990	-3.58	-2.54	2.42	-1.04	6.00
1989	-	-1.69	-	-	-
Average				-0.26	-8.67***
Std. error				0.88	2.26
t-test				-1.27	-16.68

*** Significant at or above the 0.01 level
** Significant at the 0.05 level
* Significant at the 0.10 level

$H1_0$. Moreover, that obtaining such a kind of result in this study seems to be, to large extent, related to the imbalance between the two portfolios in terms of the number of samples included in each portfolio.[36] But on the other hand, the strong evidence of the prior-year monthly return difference existing between the distressed loser and the distressed winner portfolio suggests that the sample size of distressed firm year per se is sufficient for statistical analysis. Therefore, it should have nothing to do with the fact that the momentum effect is found nonexistent among financially distressed firms.

In summary, the results obtained from above analysis do not provide any evidence showing that the market tends to underreact to financial distress risk nor confirm Agarwal and Taffler's (2008) argument on the momentum effect being specifically linked with distress risk. However, while the momentum effect is truly found absent from the group of financially distressed sample firms, no conclusion regarding the existence of distressed firm's underperforming phenomenon can be made yet because it is very likely that the failure of rejecting null Hypotheses $H1_0$ is due to nothing else but the limitation of the sample collection of this study.

6.2.3. Robustness Checks

Following Agarwal and Taffler (2008), all sample firms are required to have positive book value as mentioned in the Sample Selection and Data Section, firstly, to eliminate the problem which would be otherwise encountered during a portfolio formatting process in which the book-to-market equity becomes one of the factors that portfolio formation is based on; and secondly, to ensure that the cross-sectional regression analysis employed in Agarwal and Taffler's (2008) study can be also carried out in this study. However, based on the way how book value of a firm is defined in Agarwal and Taffler's (2008) study, which is computed as book value of equity (excluding preference capital) plus deferred taxes less minority interest, it is not impossible for a firm to have negative book value.

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[36] 322 firm years in distressed loser portfolio versus 1507 firm years in non-distressed loser portfolio (See Panel C in Table II).

During the sample period of this study, the number of negative book value firms observed on a yearly basis ranges from minimum 1 (1989) to maximum 41 (2007), and the average observations of such firm is about 19 per year. Most of those firms are determined to be in a financially distressed status by Altman's (1968) z-score. Hence, an obvious drawback of intentionally excluding firms of such kind from the sample group is that the already existed big imbalance in sample size between distressed and non-distressed samples has been further extended due to the decrease in the number of qualified distressed firm observations. Sample imbalance between two different sample classes may have great influence on any cross-comparison analysis, and consequently the analytical results are likely to be produced with poor predictive accuracy, which is the case occurred during the investigation on the market reaction to distress risk in this study. Furthermore, irrespective to the problem of sample imbalance, there might be an even more serious problem with the results obtained from the analysis focusing on the distressed sample group alone: since most likely those distressed firms with negative book value are the representatives for the worst distressed class in the market, even if the sample base remains sufficient for statistical analysis of that specific group after the exclusion, the analysis conducted on this post-exclusion basis may only be able to introduce biased estimates which are not considered to be valuable in terms of representing the market's general situation.

In order to ensure that the conclusions to be made in this study are independent from any impacts of the restrictive rule applied in the sample selection process with respect to sample firms' book value, the three sets of analysis are re-run for robust checking on a renewed set of samples which also contains all the firms with negative book value in addition to the other previously qualified sample firms. In the previous tests, the major problem with including negative-book-value firms as sample firms is that, if portfolio formation needs to be based on sample firm's book-to-market factor, the firms with negative book value, and therefore negative book-to-market ratio, would be automatically sorted into the lowest book-to-market quintile, even though as matter of fact, firms of that kind are much more like the firms in the highest book-to-market quintile in terms of their financial health status. Therefore to solve this problem in the retests, when it comes to forming portfolios based on book-to-market factor, all firms with negative book-to-market equity are not sorted into the lowest book-to-market quintile following an ascending order; instead, they are treated same as firms with high book-to-market equity, and put into the highest book-to-market quintile. As for the other two tests in which the relationship between value effect and distress risk is not the concern, the two sets of ten portfolios, namely the ten portfolios sorted on size and Altman's (1968) z-score and the ten portfolios sorted based on prior-year return and Altman's (1968) z-score, are formed in the same way as done before

The retest results (provided as appendices at the end of this study) show that the results obtained earlier in this study regarding the test on null Hypothesis $H1_0$ through $H4_0$ are still robusted even after the inclusion of negative-book-value firms in the sample group. Besides that still no convincing evidence is found on the market reaction to distress risk, my findings with respect to the previously suggested relationship between distress risk and the three market anomalies, i.e. the size effect, the value effect and the momentum effect, stay consistent also on the renewed sample basis.

6.3. Cross-Sectional Regression Analysis

The series of univariate analyses done in the previous sections have provided us some answers regarding the relationship between distress risk and the three widely explored market anomalies, i.e. size, value and momentum effect. While Agarwal and Taffler's (2008) argument about the nonexistent link between distress risk and both size and value effect has been further supported by the results obtained based on the sample of this study, a reconciliation is not achieved between the U.S. market-based evidence and the conclusion made in Agarwal and Taffler's (2008) UK based study which suggests that the distress risk is the driving force behind the momentum anomaly. The market underreaction hypothesis (the markets underreacts to financial distress risk) argued by Dichev (1998) and others has not yet got unconfirmed, but if assuming that is true, the reason why the same kind of evidence explored by Agarwal and Taffler (2008) is not found in this study might be because the connection between the momentum effect and distress risk is dependent on some market-specific factor rather than a universally accepted law. On the other hand however, it is also possible that there is indeed such a link existing in the U.S. market as well, but because its degree of sharpness is not independent from firm size and book-to-market equity, the lack of control for the two factors in the previously conducted univariate analysis might have hindered the revealing of the proposed connection between the momentum effect and distress risk. For this reason, a multivariate analysis is carried out in this section in which the above mentioned interference in the investigation on the link between the momentum effect and distress risk is also appropriately dealt with.

Applying the four-way sorting methodology introduced in earlier section, twenty four portfolios are formed based on firm size, book-to-market equity, prior-year returns and financial health status represented by Altman's (1968) z-score. Summary statistics for the twenty four portfolios are provided in Table VIII. Panel A presents the average excess monthly return on each portfolio. Underperformance of distressed firm (distressed portfolio earns lower excess monthly return than the equivalent non-distressed portfolio) is detected after size, book-to-market factors are further taken control, and seems to be specifically concentrating among firms with lower prior-year returns. Seven out of twelve pairs of vertical comparison have shown that a previous loser keeps earning lower return than previous winner. However, this medium-term continuation of stock return phenomena is not only detected among distressed firms. In fact, based on the information given in the table, it seems that the phenomenon is equally likely to appear among financially distressed firms as appearing among healthy firms; only that it is just more apparent in the former case (the return gap between previous loser and winner portfolio is bigger if they are in the financially distressed category). Hence, again my finding does not reconcile with Agarwal and Taffler's (2008) argument about the specific relationship between the momentum effect and distress risk. Panel B presents the estimated average beta for each portfolio. Distressed portfolios uniformly have higher beta than the equivalent non-distressed portfolios except for the prior-year loser portfolio with small size and low book-to-market equity (the first portfolio in the upper left corner). On this basis, the finding in the previous section is further confirmed. That is, distressed firms are not less risky than non-distressed firms. The information about the average size and the book-to-market equity of each portfolio provided in Panel C and D reveals that, overall speaking, the goal of controlling for size and book-to-market equity, has been successfully achieved through the application of four-way sorting method.[37] Last but not least, the prior-year portfolio returns presented Panel E shows that there is a bigger variance in return among distressed firm

[37] The exceptionally big average market capitalization of prior-year distressed loser in the large size, middle-high book-to-market category is mainly driven by the business giant General Electric Company.

Table VIII

Summary Statistics – Size, Book-to-Market, and Z-Score Portfolios

At the end of June of each year from 1989 to 2008, all the stocks in the sample are ranked on market capitalization and grouped into two portfolios, independently ranked on B/M, and grouped into three portfolios and independently ranked on prior-year return and grouped into two portfolios. The stocks are also independently allocated to two groups based on whether their latest available z-score is smaller or larger than 1.81. Twenty-four portfolios are then formed at the intersection of size, B/M momentum, and z-score. Portfolios are rebalanced at the end of June each year. B/M is computed as the ratio of book value of equity (excluding preference capital) plus deferred taxes less minority interests from the latest available accounts divided by the market value of equity on June 30. Average monthly excess return is the time-series average of the difference between monthly stock returns and the one-month Treasury bill rate observed at the beginning of the month. Portfolio betas are the sum of slopes in the regression of the return on a portfolio on the current, prior, and next month's market returns. Average size, average B/M, and average momentum are the time-series averages of monthly averages of market capitalization, B/M, and prior 11-month returns (excluding June), respectively, for stocks in the portfolio at the end of June of each year. Negative B/M stocks are excluded.

Size	Prior-Year Return	Low B/M		Medium B/M		High B/M	
		z<1.81	z>1.81	z<1.81	z>1.81	z<1.81	z>1.81
		Panel A. Average Excess Monthly Returns (%)					
	Low	-4.38	-0.83	-2.27	-0.81	-1.62	-0.87
Small	High	-0.29	-0.47	-2.76	-0.33	0.21	0.01
	Low	-0.47	-0.19	-2.53	-0.26	0.38	0.19
Large	High	-0.17	-1.37	-1.05	-0.56	-0.35	-0.76
		Panel B. average Beta					
	Low	1.01	1.22	1.35	1.26	1.24	1.22
Small	High	1.43	1.25	1.32	1.08	1.55	1.10
	Low	1.37	1.03	1.20	1.18	1.23	0.95
Large	High	1.11	1.05	1.26	1.08	1.01	0.71
		Panel C. Average Market Capitalization ($m)					
	Low	244.13	375.36	455.61	398.61	287.89	276.64
Small	High	390.21	382.21	358.71	409.78	321.65	288.52
	Low	42745.89	14213.05	25623.63	7657.15	6740.72	3201.97
Large	High	30223.14	14090.55	16017.13	6789.82	5382.12	3731.76
		Panel D. Average B/M					
	Low	0.11	0.11	0.39	0.43	1.26	1.02
Small	High	0.12	0.10	0.38	0.41	1.00	0.90
	Low	0.10	0.11	0.42	0.40	0.95	0.85
Large	High	0.11	0.10	0.42	0.37	0.86	0.78
		Panel E. Average Monthly Prior-Year Monthly Returns (%)					
	Low	-0.97	-0.70	-0.84	-0.31	-1.16	-1.05
Small	High	6.13	5.29	5.80	4.14	4.30	3.13
	Low	-0.76	-0.31	-0.47	-0.30	-0.52	-0.77
Large	High	3.49	3.32	3.12	2.77	2.44	2.19

stocks than among non-distressed firm stocks. The prior-year market losers are financially distressed firms, and so are the prior-year market winners. A series of Fama and MacBeth (1973) cross-sectional regressions are run on the 24-portfolio basis next. Specifically, portfolio's monthly return is regressed on different combinations of six explanatory variables, i.e. market factor, size factor, book-to-market factor, momentum factor, distress risk dummy variable and an interaction dummy between momentum and distress risk. Regressions are run on a monthly basis from July 1989 to June 2009 and portfolios are rebalanced once a year. Starting with following Agarwal and Taffler's (2008) methodology, 12-month portfolio observing period is taken in each year, meaning that each regression model is run twelve times a year from the first month after portfolio formation date till the month before the portfolio rebalancing date. On this basis, the final coefficient estimate of an explanatory variable in each regression model is computed as the average of a total of 240 estimated coefficient samples, every one of which is derived from each single monthly-based regression analysis for the respective variable over the entire sample period. Unfortunately, however, the cross-sectional regression results based on 12-month portfolio observing period seem hard to be able to provide a satisfactory basis for any further analysis or discussion on the concerned topic, i.e. the link between momentum effect and distress risk, because except for the constant α and r_2 – the estimated coefficient of size variable $\ln(SIZE_{it-1})$, none of the rest of explanatory variables are able to obtain a statistically significant coefficient.[38] While there might be various underlying causes for this unexpected outcome, one of the potential causing factors that is relatively more flexible for change is the portfolio observing period. For this reason, I decide to shorten the portfolio observing period from the original one-year span to a first-half-year span to see whether this manipulation would make any differences to the regression results. All the estimated coefficients for the respective variables derived on this later basis are reported in Table IX:

As shown in Table IX, the estimated coefficients (γ_5) of the distress risk dummy variable $z(0/1)$ are uniformly negative in all six sets of regression analysis, and all obtained values are statistically significant at the 0.05 level. Moreover, as the regression model is further refined (the regression analysis takes more control for the other explanatory variables), the estimated

[38] To save some space in the main text, the results derived from this set of regression analyses are not presented here, but a summary of the results is enclosed as an appendix (Appendix II) in the end of this study.

Table IX

Cross-Sectional Regression Results

At the end of June of each year from 1989 to 2008, all the stocks in the sample are ranked on market capitalization and grouped into two portfolios, independently ranked on B/M, and grouped into three portfolios and independently ranked on prior-year return and grouped into two portfolios. The stocks are also independently allocated to two groups based on whether their latest available z-score is smaller or larger than 1.81. Twenty-four portfolios are then formed at the intersection of size, B/M momentum, and z-score. Portfolios are rebalanced at the end of June each year. B/M is computed as the ratio of book value of equity (excluding preference capital) plus deferred taxes less minority interests from the latest available accounts divided by the market value of equity on June 30. To avoid undue influence of outliers on the regressions, the smallest and largest 1% of the observations on B/M are excluded. Portfolio betas are the sum of slopes in the regression of the return on a portfolio on the current, prior, and following month's market returns. The estimated Fama-MacBeth (1973) regression (Equation 3):

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}\ln(size_{it-1}) + \gamma_{3t}\ln(B/M_{it-1}) + \gamma_{4t}Mom_{it-1} + \gamma_{5t}z(0/1)_{it-1} + \gamma_{6t}z(0/1)_{it-1} * Mom_{it-1} + \varepsilon_{it}$$

where R_{it} is the equally weighted return on portfolio *i* during month *t* and R_{Ft} is the one-month Treasury bill rate at the beginning of month *t*. Here β_{it-1} *is* the beta of portfolio *i* estimated at the portfolio formation date. $ln(size_{it-1})$ and $ln(B/M_{it-1})$ are the natural logarithms of average of market capitalizations and average of book-to-market ratios, respectively, of stocks in portfolio *i* at the portfolio formation date. Mom_{it-1} is the average monthly return over the 11 months from July year *t-1* to May year *t* prior to the month of portfolio formation of all the stocks in portfolio i. Here $z(0/1)_{it-1}$ is equal to 1 if the latest available Z-Score is smaller than 1.81, 0 otherwise. The slopes are estimated by Fama-MacBeth (1973) cross-sectional regressions for each of the first six months after portfolio formation from 1989 to 2008. Figures in parentheses are the respective *t-statistics*. Negative book-to-market stocks are excluded.

Model	alpha	r1	r2	r3	r4	r5	r6
i	0.42	-0.16				-0.55**	
	(0.74)	(-0.57)				(-2.04)	
ii	-0.26	-0.18	0.05	0.02			
	(-0.26)	(-0.58)	(0.47)	(0.16)			
iii	0.01	-0.17	0.05	0.04		-0.57**	
	(0.01)	(-0.52)	(0.53)	(0.29)		(-2.10)	
iv	-0.54	-0.18	0.05	0.09	0.16**		
	(-0.53)	(0.56)	(0.52)	(0.64)	(2.39)		
v	-0.34	-0.10	0.05	0.09	0.18***	-0.60**	
	(-0.33)	(0.30)	(0.45)	(0.58)	(2.70)	(-2.24)	
vi	-0.37	-0.11	0.07	0.16	0.18***	-0.66**	-0.03
	(-0.36)	(0.32)	(0.67)	(1.08)	(3.46)	(-2.33)	(-0.33)

*** Significant at or above the 0.01 level
** Significant at the 0.05 level
* Significant at the 0.10 level

coefficient of the dummy variable becomes more negative and statistically significance is also entrenched. These results clearly demonstrate a negative correlation between stock return and Altman's (1968) z-score, suggesting that there is indeed evidence found within the range of the samples of this study against null Hypothesis $H1_0$ by showing that the market underreacts to distress risk rather than take it into account when doing asset pricing. On this basis, therefore, my results are not only consistent with Agarwal and Taffler's (2008) finding but also further confirm the market underreaction story stood by Beaver (1968), Dichev (1998) and Campbell, Hilscher, and Szilagyi (2006) etc..

Seen from Table IX, neither statistically significant size nor value effect has been detected through the sets of Fama and MacBeth (1973) cross-sectional regression analysis – the estimated coefficients for both variables in the regression model are determined to be insignificant from zero.[39] Several previous studies have reported that the size effect has been weakened in recent years, but the value effect have been staying consistently strong (e.g., Fama and French, 1992; Roll, 1995). This trend has also been confirmed by Agarwal and Taffler's (2008) UK-market-based study. Furthermore, it has been found in the series of univariate analyses conducted in the earlier section that these two market anomalies do exist among the samples of this study.

Therefore, given all these as background information, it is a little surprising that no significant coefficient for the size variable and book-to-market variable, particularly the later one, is derived from the sets of Fama and MacBeth (1973) cross-sectional regression analysis. On the other hand, however, the underlying reason for obtaining such results is not that hard to think of after all. The failure of finding strong evidence of size and value effect may be a consequence of the coefficient sample size provided by this study being less than sufficient for a successful Fama and MacBeth (1973) cross-sectional regression analysis in terms of proving the existence of size and value effect. More specifically, since the sample group for every single regression analysis is formed by only 24 sets of portfolio-based data, there is likely to be a big variance in the estimated coefficient obtained from each individual regression analysis. Under this circumstance, in order to obtain a statistically significant coefficient estimate in the end, a long sample period is

[39] Nevertheless, the size effect has been detected in the Fama and MacBeth (1973) cross-sectional regression analyses when one-year portfolio observing time is used (See: Appendix II).

especially required to ensure a sufficient sample size for the statistical analysis. However, while Agarwal and Taffler (2008) managed to build up a sample base with sample coefficients obtained from 288 monthly-based regressions for the analysis (in other words, there are 288 samples contained in the sample group for the coefficient estimation), the coefficient sample group in this study only includes 120 individual coefficient samples. If the lack of coefficient samples is truly responsible for not finding strong evidence of value effect through the Fama and MacBeth (1973) cross-sectional regression analysis conducted in this study, then presumably, the estimated coefficient of the book-to-market variable in the regression model will eventually become significantly positive once a long enough timeline is available for the analysis. Furthermore, as long as there are sufficient coefficient samples forming the sample base, a significantly negative coefficient is also very likely to be derived for the size variable (the size effect) based on the sample of this study.[40]

The financial distress factor hypothesis of Chan and Chen (1991) and Fama and French (1992) has been rejected by the empirical findings obtained from the previous univariate analyses. This conclusion is further certified in the Fama and MacBeth (1973) cross-sectional regression analysis. Firstly, the financial distress factor hypothesis suggests a positive relationship between stock return and distress risk, but as discussed already, an opposite correlation between stock return and Altman's (1968) z-score is found here instead. Secondly, part of the essential argument of the financial distress factor hypothesis is that firm size and book-to-market equity are two proxies for distress risk. If that is true, presumably the coefficient estimates for the two variables would be negatively affected by an insert of distress risk variable into the regression model. However, it is shown in Table IX that the coefficient estimates obtained for the size variable and the book-to-market variable (r_2, r_3) using Model iii have turned out to be very close to the respective coefficients obtained using and Model ii (the coefficient of the size factor is 0.05 in both models; the coefficient of the book-to-market variable is 0.02 in Model ii and 0.04 in Model iii). Furthermore, although a comparison of the statistical significance level of the two variables' coefficients determined by Model ii and Model iii can hardly provide any further valuable information because of the uniformly low *t*-test results enclosed with the two

[40] This argument is relied on the fact that once the coefficient sample size is increased to 240 when one-year period portfolio observing period is taken, the Fama and MacBeth (1973) cross-sectional regression analysis is able to obtain significantly negative coefficient for the size variable as shown in the Appendix II at the end of this paper.

coefficients in both models, the upward change in *t*-test results of the two concerned coefficients from Model ii and Model iii still implicitly disapprove the argument that firm size and book-to-market equity can be considered as proxies for distress risk.

The momentum effect, whose existence the previous univariate analysis was not able to uncover, is shown strong in all three regression models (Model iv, v and vi), where the momentum variable Mom_{t-1} is included as an explanatory variable. The estimated coefficient (r_4) in the three regression models is uniformly positive, and statistically significant above the 0.01 level. These results clearly suggest a stock return's medium-term continuation phenomenon. That is, a stock's previous return pattern tends to be carried on in the same direction for a period of time in the future (e.g. one year), and during that time the previous winner will continue to be the winner while the previous loser will stay as the loser. Unfortunately however, in contrast to the results reported in Agarwal and Taffler's (2008) paper, the estimated coefficient of the momentum variable did not shrink in size after the distressed risk dummy variable $z(0/1)$ is added into the regression model (Model v and vi), neither does its statistical significance level. As matter of fact, the coefficient of the momentum variable and its *t*-test result are both improved instead from 0.16 to 0.18 and from 2.70 to 3.46 respectively, suggesting that the inclusion of the distress risk dummy variable in the model only helped refine the regression model so that the correlation between stock's current and past return gets more clearly revealed. Based on these results, the momentum return does not seem to be correlated with distress risk through the market underreaction to this specific risk – the way which is proposed by Agarwal and Taffler (2008). Furthermore, in Model vi where the momentum effect is shown to be the strongest (r_4 = 0.18, t = 3.46), the coefficient estimate of the interaction dummy variable is determined to be insignificantly different from zero (r_6 = -0.03, t = 0.33). Therefore, this finding again implies that the momentum effect is indeed generated in the samples of this study, but it is really hard to say that it has anything to do with distress risk but some other factor(s).

To summarize, in this section a multivariate analysis is conducted on a four-way sorted 24-portfolios basis using the Fama and MacBeth (1973) cross-sectional regression method, aiming at retesting the market reaction to distress risk and the link between momentum effect and distress risk. Although a satisfied base for any meaningful analysis and discussion on the topics of interest cannot be established by exactly following Agarwal and Taffler's (2008) analysis design, once the original one-year portfolio observing time is shortened to half-year span, evidence of momentum effect and market reaction to distress risk and are successfully obtained. The main findings are as follow: the market underreaction to distress risk is evidenced by the significantly negative estimated coefficient obtained for the distress risk dummy variable; momentum effect is also found existing among the samples of this study, but the Agarwal and Taffler (2008) suggested link between momentum effect and distress risk does not seem to be held on the U.S market basis, because the momentum effect did not vanish as expected as a result of the introduction of distress risk dummy variable into the regression model. Furthermore, although not being the focus, the connection between distress risk and the other two market anomalies, namely the size effect and the value effect is also retested again as by-products during the cross-sectional analyzing process. Both size effect and value effect are still found not significantly connected to distress risk as neither the estimated coefficient nor the respective *t*-test result of both variables is significantly affected by the new inclusion of distress risk dummy variable in the regression model. Therefore, same as the conclusion drawn from the previous univariate analysis, the financial distress factor hypothesis of Chan and Chen (1991) and Fama and French (1992) cannot be accepted based on the sample of this study.

6.3.1 Robustness Check with a New Cut-off Point

Since the results derived from the series of Fama and MacBeth (1973) cross-sectional regression analyses which are conducted based on the initially chosen firm financial health status determination standard (z = 1.81) are found hard to reconcile with Agarwal and Taffler's (2008) conclusion regarding distress risk being the driving force behind the momentum effect, a further step is taken in this section to find out whether this sample-based finding of this study is sensitive to the choice of the critical Z value which is more possibly exposed to a subjective decision.

It is worth mentioning that Altman (1968) did suggest an optimal Z value (z = 2.675) as a cut-off point in his study aiming at assisting people with need to more easily determine a firm's financial status. The cut-off point at 2.675 was proposed because it was the middle point of the z-score

range between 2.67 and 2.68, the area in the "zone of ignorance" where the number of misclassifications was found minimum based on the initial sample used in that study. However, in order to be as precise as possible in terms of bankruptcy prediction, Altman's (1968) z-score 1.81 rather than 2.675 is initially chosen as the cut-off point in this study to separate financially distressed firms (z-score below 1.81) from other healthy firms mainly because in the initial sample of Altman's (1968) study firms having z-score below 1.81 all actually went bankruptcy.
A consequence of the initial decision of holding z = 1.81 as the cut-off point is that a noticeable difference in sample formation is realized between this and Agarwal Taffler's (2008) study: there are only 13.0% of the entire sample group of this study identified as samples at distress risk, which is just a bit over half of the proportion (24.5%) that distressed samples took up in Agarwal and Taffler's (2008) sample collection. It is possible that the inconsistency found between these two studies regarding the existence of a link between momentum effect and distress risk is simply due to this difference. If that really is the case, once the sample group formation in this study becomes more comparative with that the original study is based on, the results derived from the series of cross-sectional regression analyses run in the former section are expected to be found more compromised with Agarwal and Taffler's (2008) conclusion.

The series of Fama and MacBeth (1973) cross-sectional regression analyses are repeated after replacing the initially used cut-off point z = 1.81 with the higher z-score 2.675, holding other things unchanged. Z value of 2.675 is considered as another reasonable cut-off point for two reasons: beside that it is the optimal cut-off point proposed by Altman (1968), another important reason is that if the critical point chosen is loosened up to 2.675 instead, the distressed sample's proportion in the entire sample group would be increased to around 27%, which would then make the formation of the sample base of this study more comparable with that Agarwal and Taffler's (2008) study was based on. The retest results are presented in Table X. As it has already been found in the former section that the main purpose of conducting the Fama and MacBeth (1973) cross-sectional regression analysis is better served if half-year portfolio observing period is taken, all the retest results presented in that table are obtained on that basis.[41]

[41] The retest has also been conducted on one-year observing period basis. The unreported retest results (available upon request) show that when 24 portfolios' monthly returns are observed with one-year span, same as before, neither the momentum variable nor the distress risk dummy variable in the model is able to obtain statistically significant coefficient.

Table X

Cross-Sectional Regression Results (Using z = 2.675 as the Cut-off Point)

At the end of June of each year from 1989 to 2008, all the stocks in the sample are ranked on market capitalization and grouped into two portfolios, independently ranked on B/M, and grouped into three portfolios and independently ranked on prior-year return and grouped into two portfolios. The stocks are also independently allocated to two groups based on whether their latest available z-score is smaller or larger than 2.675. Twenty-four portfolios are then formed at the intersection of size, B/M momentum, and z-score. Portfolios are rebalanced at the end of June each year. B/M is computed as the ratio of book value of equity (excluding preference capital) plus deferred taxes less minority interests from the latest available accounts divided by the market value of equity on June 30. To avoid undue influence of outliers on the regressions, the smallest and largest 1% of the observations on B/M are excluded. Portfolio betas are the sum of slopes in the regression of the return on a portfolio on the current, prior, and following month's market returns. The estimated Fama-MacBeth (1973) regression (Equation 3):

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}\ln(size_{it-1}) + \gamma_{3t}\ln(B/M_{it-1}) + \gamma_{4t}Mom_{it-1} + \gamma_{5t}z(0/1)_{it-1} + \gamma_{6t}z(0/1)_{it-1} * Mom_{it-1} + \varepsilon_{it}$$

where R_{it} is the equally weighted return on portfolio *i* during month *t* and R_{Ft} is the one-month Treasury bill rate at the beginning of month *t*. Here β_{it-1} *is* the beta of portfolio *i* estimated at the portfolio formation date. *ln(size$_{it-1}$)* and *ln(B/M$_{it-1}$)* are the natural logarithms of average of market capitalizations and average of book-to-market ratios, respectively, of stocks in portfolio *i* at the portfolio formation date. Mom_{it-1} is the average monthly return over the 11 months from July year *t-1* to May year *t* prior to the month of portfolio formation of all the stocks in portfolio i. Here $z(0/1)_{it-1}$ is equal to 1 if the latest available Z-Score is smaller than 2.675, 0 otherwise. The slopes are estimated by Fama-MacBeth (1973) cross-sectional regressions for each of the first six months after portfolio formation from 1989 to 2008. Figures in parentheses are the respective *t-statistics*. Negative book-to-market stocks are excluded.

Model	alpha	r1	r2	r3	r4	r5	r6
i	0.18	0.11				-0.23	
	(0.36)	(0.81)				(-0.88)	
ii	1.00	0.05	-0.06	0.34*			
	(1.26)	(0.17)	(-0.80)	(1.76)			
iii	1.35	0.19	-0.09	0.53***		-0.24	
	(1.67)	(0.69)	(-1.23)	(2.95)		(-1.21)	
iv	0.43	0.27	-0.12	0.28**	0.30***		
	(0.52)	(0.86)	(-1.43)	(2.38)	(4.75)		
v	0.30	0.34	-0.09	0.30**	0.29***	-0.28	
	(0.36)	(1.03)	(-1.07)	(2.58)	(4.63)	(-1.45)	
vi	0.14	0.47	-0.10	0.22*	0.23***	-0.31	0.04
	(0.17)	(1.42)	(-1.17)	(1.90)	(3.82)	(-1.38)	(0.54)

*** Significant at or above the 0.01 level
** Significant at the 0.05 level
* Significant at the 0.10 level

The main findings are as follow: firstly, taking Z value of 2.675 as the new cut-off point to distinguish financially distressed samples from normal samples, both size and book-to-market variable's coefficients (r_2 and r_3) derived from the Fama and MacBeth (1973) cross-sectional regression analysis as well as their *t*-test results become more comparable with the respective results reported in Agarwal and Taffler's (2008) study. In addition to that, the same as the before, no significant change in the both coefficients is found taken place after introducing the distress risk dummy variable into the regression model.

Secondly, a negative correlation between distress risk and stock return has been evidenced in the former test, but the estimated coefficient (r_5) of the distress risk dummy variable becomes less negative than the respective estimated coefficient reported in Table IX, which was obtained when Z value of 1.81 was used as the cut-off point. Moreover, another fact regarding the set of estimated coefficients for the distress risk dummy variable is that although their values turned out to be very close to the respective results obtained by Agarwal and Taffler (2008) after the new firm financial health status determination standard is employing, a negative correlation between distress risk and stock return as suggested by Agarwal and Taffler's (2008) results cannot be pronounced on this basis because none of the negative values is determined to be statistically significant by their enclosed *t*-test results. Since based on Altman's (1968) finding, Type II error, i.e. a non-distressed firm is misclassified into the distressed category, is more likely to occur when the cut-off point is set at z = 2.675, the vanishing in negativity and statistical significance of the distress risk dummy variable's coefficient in the retest should be due to the disturbance of the noise introduced into the distressed sample group by the new employed firm financial health status determination standard.

The third and also the most important finding from the results presented in Table X is that, the momentum effect is again found very strong after grouping all samples with the new firm financial health status determination standard (all three results derived using Model iv, v and vi are uniformly positive above the 0.01 significance level), however, the presence of momentum effect is not necessarily dependent on the market reaction to distress risk. Comparing the estimated coefficient of the momentum variable derived using Model iv, v and vi, it is true that both of the value and its *t*-test result of the estimated coefficient of the momentum variable have been slightly decreased after introducing the distress risk dummy variable into the regression model, but this change was taken place under the circumstance that the market underreaction to distress risk factor is shown statistically absent (the negative coefficient of the distress risk dummy variable is not insignificantly different from zero). Moreover, the independence between momentum effect and distress risk is further confirmed by the fact that the interaction dummy variable $z(0/1)_{t-1}$ in Model vi again failed to obtain a significantly positive the coefficient in the retest while the momentum variable's coefficient has kept staying strong. On this basis, therefore,although with the new cut-off point the distressed sample's proportion in the entire sample group of this study has been increased to a comparable level to that in Agarwal and Taffler's (2008) study, the U.S.-market-based Fama and MacBeth (1973) cross-sectional regression analysis is still unable to provide similar evidence to show that momentum effect is specifically connected to the market underreaction to distress risk as suggested by Agarwal and Taffler (2008).

This section is devoted to examine the sensitivity of the cross-sectional regression results to the choice of the cut-off Z value determining a firm sample's financial health status. To conclude this section, after changing the critical Z value from 1.81 to 2.675, no drastic change is found in the results derived from the repeated Fama and MacBeth (1973) cross-sectional regression analysis. The inconsistency found between this and Agarwal and Taffler's (2008) study regarding the existence of a link between the momentum effect and distress risk is robust.

7. Summary and Further Discussion

"Financial distress" defines a situation in which a business entity encounters difficulties to fulfill its promises to creditors in time. A long-lasting financial distress problem will eventually lead a firm to enter a bankruptcy process, and in which case both debt and equity investors are very likely to be exposed to considerable financial looses. For its potential big influence on the market and various market players, not only always being under the market practitioners' close watch, financial distress risk, as a topic, has also been constantly gaining attention from the academic world, especially after 1980 since when the rate of insolvency and business failure has dramatically increased.

In several previous researches, the main interest in distress risk has been centralized on investigating its impact on stock return pattern. This paper is devoted as a continuous study in this specific area. Firstly because so far among the previous studies a consensus has not been achieved yet in terms of whether and how the market reacts to distress risk. On one hand, scholars, such as Chan and Chen (1991) and Fama and French (1992) among uphold that the market reaction to distress risk reconcile with the market efficiency theory: they believe that there is a connection between a firm's financial health status and its size and/or book-to-market equity; and the higher returns to small stocks and value stocks (stocks with high book-to-market equity) is essentially due to the fact that the firms behind those stocks are relatively financially distressed. It is equal to say, based on this claim, that size effect and value effect – the two well-known market anomalies are nothing special but just another form showing that how the market is playing following the risk-return trade-off principle. On the other hand, Dichev (1998) and Campbell, Hilscher, and Szilagyi (2006) among others argue for market underreaction story: their empirical-based research could not provide evidence to suggest that either size or book-to-market factor is able to proxy for distress risk; at the same time, they found out that rather than outperforming, firms tend to earn lower stock returns when they are in financial distress. Furthermore, for the first time Agarwal and Taffler (2008) claimed in their recent UK-marked-based study that the generation of momentum effect is connected with the market underreaction to distress risk, and since then a similar kind of investigation has not yet been taken in any other market. However, it is definitely worth doing that to examine the applicability of this new proposed theory under different circumstances, which is another reason for conducting this U.S.-market-based study.

Taking Agarwal and Taffler's (2008) methodologies as basis, the connection between distress risk and three market anomalies, i.e. size effect, value effect and momentum effect, is examined respectively on both univariate and multivariate level. However, as this study is conducted based on U.S. market, instead of using UK-based z-score bankruptcy prediction model, the very first version of Altman's (1968) z-score model is employed to determine sample firms' financially health status. Furthermore, considering that the Altman's (1968) z-score model which was originally developed based on samples collected from manufacturing industry is later on proved to be the most effective in bankruptcy prediction within the same industry range, the sample group of this study is consisted with only publicly traded manufacturing firms. The main findings of the series of investigations are summarized as follow:

Firstly, in the univariate analysis, after taking control of distress risk factor, strong size effect is found still existing on both distressed and non-distressed side; under the same condition, value effect also does not completely disappear – at least on the non-distressed side, high book-to-market portfolio keeps on earning superior return over portfolio with low book-to-market equity. Furthermore, it is also found that neither of the estimated coefficients derived for size and book-to-market variable in the multivariate analysis is substantially affected by an introduction of distress risk factor into the regression model. On the basis, the financial distress factor hypothesis of Chan and Chen (1991) and Fama and French (1992) has to be rejected: although there might be some correlation between a firm's financial health status and its size or its book-to-market equity, the two firm factors cannot be considered as good proxy for distress risk; and consequently, the generation of higher returns on small firms and firms with higher book-to-market equity is also not necessarily connected with an existence of distress risk in firms of that kind. Second, although the results derived from the series of univariate analyses could not provide convincing evidence in terms of the market reaction to distress risk, strong negative correlation between distress risk factor and stock return has been found during the Fama and MacBeth (1973) cross-sectional regression analysis (multivariate analysis) when portfolio observing period is fixed with half year. Therefore, irrespective to the different portfolio observing period considered in this study and in Agarwal and Taffler's (2008) paper, my finding based on the cross-sectional regression analysis regarding the market reaction to distress risk is consistent with Agarwal and Taffler's (2008) finding, the market tends to underreact to distress risk. On this basis, the market underreaction story claimed by Beaver (1968), Dichev (1998) and Campbell, Hilscher, and Szilagyi (2006) gets further confirmed. Thirdly, even though the Fama and MacBeth (1973) cross-sectional regression results have shown strong existence of the momentum effect, unlike Agarwal and Taffler's (2008) finding, the generation of momentum effect is found quite independent from the market underreaction to distress risk based on the sample of this study as the introduction of distress risk factor into the regression model hardly showed any impact on smoothing the medium-term continuation of stock return phenomenon. As a result, Agarwal and Taffler's (2008) proposed new theory regarding the market underreaction to distress risk being the cause of momentum effect is unfortunately disapproved by my U.S.-market-based empirical evidence.

Probably, the inconsistency found between this study and Agarwal and Taffler's (2008) study in answering the question whether the momentum effect is driven by distress risk is due to the fact that these two studies are conducted in different markets. If that is really the case, negative answer to the question given by this U.S.-market-based study would suggest that Agarwal and Taffler's (2008) new theory regarding the connection between momentum effect and distress risk perhaps is not universally applicable, its acceptance may vary from one market to another. It therefore would be interesting to have Agarwal and Taffler's (2008) this proposed theory further tested in some other different markets in future studies – only after that, it will become clearer whether the Agarwal and Taffler's (2008) new theory is more likely to be generally accepted or denied.

On the other hand, however, it is also possible that Agarwal and Taffler's (2008) theory is actually correct and applicable in the U.S. market as well; but due to some technique-related factor, this study has been prevented from providing empirical evidence to support this new theory. Under this assumption, there are at least two limitations in the nature of the currently employed Altman's (1968) z-score model in this study worth of discussing. One limitation is related to the fact that this is a specific industry-focused model. Its rate of accuracy in bankruptcy prediction, as notified in some earlier studies (Grice and Ingram, 2001; Agarwal and Taffler, 2007), decreases evidentially when the original model is applied to firms from non-manufacturing industries. For this reason, while the sample of Agarwal and Taffler's (2008) study has covered almost all industries except for financial sector, the sample selection in this study is restricted to only manufacturing firms. Consequently, the evidence found on this limited basis at the best can lead to making a conclusion for the manufacturing industry rather than for the U.S. market in general.[42] Another limitation in the nature of the Altman's (1968) z-score model used in this study is that this model was established almost half century ago, and ever since then great changes in both accounting standards and reporting practices have been taken

[42] Based on the initial raw data collection of this study, manufacturing firms (SIC code 1-3999 and 5000-5999) count for just half of the total amount of U.S. firms listed on NYSE, AMEX and NASDAQ.

places. As Altman's (1968) z-score model is an accounting based model, it is reasonable to believe that the effectiveness of the original model could have been much affected by some of those changes.[43] If that is the case, consequently, either the model itself or the optimal cut-off point determining financial stress conditions or both are subject to modification. Since all the analyses conducted in this study are based on the original model and critical Z valued proposed by Altman (1968), it is unknown yet after done some necessary technical updating to the bankruptcy prediction model whether the same analyses would then provide different results which become more consistent with Agarwal and Taffler's (2008) finding.

[43] Mensah (1984) pointed out that to keep the effectiveness of accounting-based models, such models may require for redevelopment from time to time, so that the changes in the economic environment to which they are being applied can be well taken into account during the model developing process.

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Website:

Kenneth R. French's data library

http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Appendix I

Table I

Size and Distress Risk in Stock Returns (Negative B/M Samples Included)

Portfolios are formed as follows: at the end of June of each year from 1989 to 2008, all the stocks in the sample are allocated to two groups based on whether their latest available z-score is smaller or larger than 1.81. The stocks are also independently ranked on market capitalization and grouped into five portfolios. Ten portfolios are then formed at the intersections of size and z-score. For each size quintile, an arbitrage portfolio labeled "Difference," long on distressed stocks and short on non-distressed stocks, is also formed. Panel A presents the portfolio summary statistics. B/M is computed as the ratio of book value of equity (excluding preference capital) plus deferred taxes less minority interests from the latest available accounts divided by the market value of equity on June 30. Average monthly excess return is the time-series average of difference between monthly stock returns and the one-month Treasury bill rate observed at the beginning of the month. Portfolio betas are the sum of slopes in the regression of the return on a portfolio on the current, prior, and next month's market returns. Average size, average B/M, and average momentum are the time-series averages of monthly averages of market capitalization, B/M, and prior 11-month returns (excluding June), respectively, for stocks in the portfolio at the end of June of each year. Panel B presents the intercepts and adjusted R^2 for each of the portfolios from the following Fama and French (1993) three-factor model (Equation 2):

$$R_{it} - R_{Ft} = \beta_1 + \beta_2(R_{Mt} - R_{Ft}) + \beta_3 SMB_t + \beta_4 HML_t \varepsilon_{it}$$

where R_{it} is the equally weighted return on portfolio i during month t, R_{Ft} is the one-month Treasury bill rate at the beginning of month t, and R_{Mt} is the value-weighted return during month t. Here SMB_t is the return on the mimicking portfolio for the size factor during month t, and HML_t is the return on the mimicking portfolio for the B/M factor during month t. Also, ε_{it} is a mean-zero stochastic error term. Data for variables R_{Mt}, SMB_t and HML_t are all taken from taken from Professor Kenneth R. French's website. Figures in parentheses are the t – statistics.

Panel A. Summary Statistics

Size	Average Market Cap ($m)		Average B/M		Average Monthly Prior-Year Return (%)		Average Beta		Average Excess Monthly Returns (%)		Difference
	z<1.81	z>1.81	z<1.81	z>1.81	z<1.81	z>1.81	z<1.81	z>1.81	z<1.81	z>1.81	
Small	67.50	80.85	0.82	0.72	2.18	1.41	1.29	1.09	2.19***	1.44***	0.75
									(3.68)	(4.34)	(1.71)
2	419.49	386.42	0.58	0.55	1.40	1.18	1.43	1.40	1.18	0.99***	0.19
									(2.70)**	(3.00)	(0.66)
3	959.82	976.43	0.53	0.41	1.37	1.35	1.33	1.16	0.53*	0.67**	-0.14
									(1.83)	(2.68)	(-0.73)
4	2582.08	2565.17	0.51	0.34	1.21	1.32	1.31	1.15	0.62	0.59**	0.03
									(1.64)	(2.56)	(0.11)
Big	41014.65	21701.55	0.45	0.24	1.20	1.34	0.96	0.84	0.46	0.45*	0.01
									(1.50)	(1.87)	(0.06)
Small-Big									1.73***	0.99***	0.73
									(3.24)	(3.24)	(1.64)

Table I (Continued)

Size and Distress Risk in Stock Returns (Negative B/M Samples Included)

Panel B. Fama and French (1993) Regression Results

Size	Intercept (β_1)			Adjusted R^2		Difference
	z<1.81	z>1.81	Difference	z<1.81	z>1.81	
Small	1.49**	0.57**	0.93*	0.20	0.63	0.01
	(2.39)	(2.31)	(1.75)			
2	-0.30	-0.30	-0.06	0.62	0.79	0.07
	(-0.75)	(-1.44)	(-0.19)			
3	-0.62**	-0.31*	-0.30	0.61	0.79	0.02
	(-2.16)	(-1.77)	(-1.15)			
4	-0.69*	-0.37*	-2.05	0.57	0.76	0.11
	(-1.79)	(-2.05)	(-0.99)			
Big	-0.59**	-0.42**	-0.30	0.69	076	0.15
	(-2.56)	(-2.72)	(-1.43)			
Small-Big	2.08***	0.99***	1.24**	0.07	0.20	0.06
	(3.20)	(3.62)	(2.20)			

*** Significant at or above the 0.01 level
** Significant at the 0.05 level
* Significant at the 0.10 level

Table II

B/M and Distress Risk in Stock Returns (Negative B/M Samples Included)

Portfolios are formed as follows: at the end of June of each year from 1989 to 2008, all the stocks in the sample are allocated to two groups based on whether their latest available z-score is smaller or larger than 1.81. The stocks are also independently ranked on B/E and grouped into five portfolios. Ten portfolios are then formed at the intersections of B/M and z-score. For each B/M quintile, an arbitrage portfolio labeled "Difference," long on distressed stocks and short on non-distressed stocks, is also formed. Panel A presents the portfolio summary statistics. B/M is computed as the ratio of book value of equity (excluding preference capital) plus deferred taxes less minority interests from the latest available accounts divided by the market value of equity on June 30. Average monthly excess return is the time-series average of difference between monthly stock returns and the one-month Treasury bill rate observed at the beginning of the month. Portfolio betas are the sum of slopes in the regression of the return on a portfolio on the current, prior, and next month's market returns. Average size, average B/M, and average momentum are the time-series averages of monthly averages of market capitalization, B/M, and prior 11-month returns (excluding June), respectively, for stocks in the portfolio at the end of June of each year. Panel B presents the intercepts and adjusted R^2 for each of the portfolios from the following Fama and French (1993) three-factor model (Equation 2):

$$R_{it} - R_{Ft} = \beta_1 + \beta_2 (R_{Mt} - R_{Ft}) + \beta_3 SMB_t + \beta_4 HML_t \varepsilon_{it}$$

where R_{it} is the equally weighted return on portfolio i during month t, R_{Ft} is the one-month Treasury bill rate at the beginning of month t, and R_{Mt} is the value-weighted return during month t. Here SMB_t is the return on the mimicking portfolio for the size factor during month t, and HML_t is the return on the mimicking portfolio for the B/M factor during month t. Also, ε_{it} is a mean-zero stochastic error term. Data for variables R_{Mt}, SMB_t and HML_t are all taken from taken from Professor Kenneth R. French's website. Figures in parentheses are the t – statistics.

Panel A. Summary Statistics

B/E	Average Market Cap ($m)		Average B/M		Average Monthly Prior-Year Return (%)		Average Beta		Average Excess Monthly Returns (5)		Difference
	z<1.81	z>1.81	z<1.81	z>1.81	z<1.81	z>1.81	z<1.81	z>1.81	z<1.81	z>1.81	
Low	23506.61	9966.82	0.07	0.07	2.99	2.09	1.40	1.18	1.48***	0.68***	0.80*
									(3.52)	(2.95)	(1.82)
2	8730.16	8469.33	0.21	0.24	2.03	2.14	0.96	1.28	1.07***	0.65**	0.41
									(3.33)	(2.64)	(1.51)
3	12372.30	3753.80	0.40	0.41	2.31	1.51	1.20	1.20	0.71***	0.52*	-0.11
									(3.03)	(1.97)	(-0.33)
4	3465.30	1604.50	0.66	0.64	1.35	0.71	1.39	1.22	0.90***	0.74**	-0.15
									(2.95)	(2.40)	(-0.55)
High	2026.54	1385.87	0.94	0.98	0.81	-0.09	1.29	1.25	1.23**	1.24***	-0.01
									(2.64)	(3.88)	(-0.05)
High-Low									-0.25	0.56**	-0.81
									(-0.46)	(2.57)	(-1.64)

Table II (Continued)

B/M and Distress Risk in Stock Returns (Negative B/M Samples Included)

Panel B. Fama and French (1993) Regression Results

B/E	Intercept (β_1)			Adjusted R^2		Difference
	z<1.81	**z>1.81**	**Difference**	**z<1.81**	**z>1.81**	
Low	0.29	-0.22	0.55	0.41	0.79	0.07
	(0.51)	(-1.30)	(1.05)			
2	0.03	-0.15	0.24	0.39	0.79	0.03
	(0.08)	(-0.93)	(0.59)			
3	-0.37	-0.32*	-0.11	0.41	0.81	0.02
	(-0.91)	(-2.06)	(-0.29)			
4	-0.38	-0.17	-0.22	0.52	0.80	0.01
	(-1.08)	(-0.99)	(-0.63)			
High	0.07	0.01	-0.09	0.55	0.74	0.02
	(0.18)	(0.04)	(-0.27)			
High-Low	-0.22	0.23*	-0.64	0.04	0.23	0.03
	(-0.42)	(1.78)	(-1.16)			

*** Significant at or above the 0.01 level
** Significant at the 0.05 level
* Significant at the 0.10 level

Table III

Prior-Year Return and Distress Risk in Stock Returns (Negative B/M Samples Included)

Portfolios are formed as follows: at the end of June of each year from 1989 to 2008, all the stocks in the sample are allocated to two groups based on whether their latest available z-score is smaller or larger than 1.81. The stocks are also independently ranked on prior-year returns and grouped into five portfolios. Ten portfolios are then formed at the intersections of prior-year returns and z-score. For each prior-year return quintile, an arbitrage portfolio labeled "Difference," long on distressed stocks and short on non-distressed stocks, is also formed. Panel A presents the portfolio summary statistics. B/M is computed as the ratio of book value of equity (excluding preference capital) plus deferred taxes less minority interests from the latest available accounts divided by the market value of equity on June 30. Average monthly excess return is the time-series average of difference between monthly stock returns and the one-month Treasury bill rate observed at the beginning of the month. Portfolio betas are the sum of slopes in the regression of the return on a portfolio on the current, prior, and next month's market returns. Average size, average B/M, and average momentum are the time-series averages of monthly averages of market capitalization, B/M, and prior 11-month returns (excluding June), respectively, for stocks in the portfolio at the end of June of each year. Panel B presents the intercepts and adjusted R2 for each of the portfolios from the following Fama and French (1993) three-factor model (Equation 2):

$$R_{it} - R_{Ft} = \beta_1 + \beta_2 (R_{Mt} - R_{Ft}) + \beta_3 SMB_t + \beta_4 HML_t \varepsilon_{it}$$

where R_{it} is the equally weighted return on portfolio *i* during month t, RFt is the one-month Treasury bill rate at the beginning of month *t*, and RM_t is the value-weighted return during month *t*. Here SMB_t is the return on the mimicking portfolio for the size factor during month *t*, and HML_t is the return on the mimicking portfolio for the B/M factor during month *t*. Also, ε_{it} is a mean-zero stochastic error term. Data for variables R_{Mt}, SMB_t and HML_t are all taken from taken from Professor Kenneth R. French's website. Figures in parentheses are the *t-statistics*.

Panel A. Summary Statistics

Prior-Year Return	Average Market Cap ($m)		Average B/M		Average Monthly Prior-Year Return (%)		Average Beta		Average Excess Monthly Returns (5)		Difference
	z<1.81	z>1.81	z<1.81	z>1.81	z<1.81	z>1.81	z<1.81	z>1.81	z<1.81	z>1.81	
Loser	2127.77	3178.76	0.77	0.64	-2.19	-1.91	1.38	1.14	1.34**	1.08***	0.26
									(2.57)	(4.15)	0.63
2	7711.01	5162.04	0.63	0.51	0.22	-0.10	1.48	1.15	0.65*	0.67**	-0.02
									(1.96)	(2.50)	-0.06
3	8980.91	5862.42	0.50	0.42	1.14	0.95	1.20	0.96	0.53	0.64**	-0.11
									(1.35)	(2.23)	-0.49
4	19999.49	4829.34	0.52	0.31	2.34	5.50	1.14	1.09	0.89**	0.76***	0.14
									(2.45)	(2.87)	0.48
Winner	6611.14	4771.98	0.40	0.32	6.58	5.49	1.47	1.32	1.21**	0.98***	0.23
									(2.63)	(3.56)	0.69
Winner-Loser									-0.13	-0.10	-0.03
									(-0.23)	(-0.39)	-0.06

Table III (Continued)

Prior-Year Return and Distress Risk in Stock Returns (Negative B/M Samples Included)

Panel B. Fama and French (1993) Regression Results

Prior-Year Return	Intercept (β_1)			Adjusted R^2		Difference
	z<1.81	z>1.81	Difference	z<1.81	z>1.81	
Loser	0.19	-0.06	0.23	0.36	0.71	0.03
	(0.35)	(-0.26)	(0.50)			
2	-0.38	-0.38**	-0.03	0.51	0.78	0.01
	(-1.14)	(-2.13)	(-0.09)			
3	-0.45	-0.35**	-0.15	0.55	0.79	0.05
	(-1.43)	(-2.30)	(-0.47)			
4	-0.19	-0.03	-0.15	0.53	0.78	0.04
	(-0.58)	(-0.21)	(-0.53)			
Winner	0.02	-0.02	-0.03	0.56	0.75	0.04
	(0.05)	(-0.07)	(-0.08)			
Winner-Loser	-0.17	0.05	-0.26	0.09	0.11	0.05
	(-0.29)	(0.18)	(-0.48)			

*** Significant at or above the 0.01 level
** Significant at the 0.05 level
* Significant at the 0.10 level

Appendix II

Cross-Sectional Regression Results (With One-Year Portfolio Observing Time)

At the end of June of each year from 1989 to 2008, all the stocks in the sample are ranked on market capitalization and grouped into two portfolios, independently ranked on B/M, and grouped into three portfolios and independently ranked on prior-year return and grouped into two portfolios. The stocks are also independently allocated to two groups based on whether their latest available z-score is smaller or larger than 1.81. Twenty-four portfolios are then formed at the intersection of size, B/M momentum, and z-score. Portfolios are rebalanced at the end of June each year. B/M is computed as the ratio of book value of equity (excluding preference capital) plus deferred taxes less minority interests from the latest available accounts divided by the market value of equity on June 30. To avoid undue influence of outliers on the regressions, the smallest and largest 1% of the observations on B/M are excluded. Portfolio betas are the sum of slopes in the regression of the return on a portfolio on the current, prior, and following month's market returns. The estimated Fama-MacBeth (1973) regression (Equation 3):

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}\ln(size_{it-1}) + \gamma_{3t}\ln(B/M_{it-1}) + \gamma_{4t}Mom_{it-1} + \gamma_{5t}z(0/1)_{it-1} + \gamma_{6t}z(0/1)_{it-1} * Mom_{it-1} + \varepsilon_{it}$$

where R_{it} is the equally weighted return on portfolio *i* during month *t* and R_{Ft} is the one-month Treasury bill rate at the beginning of month *t*. Here β_{it-1}*is* the beta of portfolio *i* estimated at the portfolio formation date. $ln(size_{it-1})$ and $ln(B/M_{it-1})$ are the natural logarithms of average of market capitalizations and average of book-to-market ratios, respectively, of stocks in portfolio *i* at the portfolio formation date. Mom_{it-1} is the average monthly return over the 11 months from July year *t-1* to May year *t* prior to the month of portfolio formation of all the stocks in portfolio i . Here $z(0/1)_{it-1}$ is equal to 1 if the latest available Z-Score is smaller than 1.81, 0 otherwise. The slopes are estimated by Fama-MacBeth (1973) cross-sectional regressions for each of the first six months after portfolio formation from 1989 to 2008. Figures in parentheses are the respective *t-statistics*. Negative book-to-market stocks are excluded.

Model	alpha	r1	r2	r3	r4	r5	r6
i	0.74*	0.11				0.07	
	(1.93)	(0.53)				(0.36)	
ii	2.24***	0.05	-0.21**	-0.07			
	(2.94)	(0.24)	(-2.56)	(-0.67)			
iii	2.26***	0.01	-0.21**	-0.08		0.09	
	(3.05)	(0.04)	(-2.52)	(-0.68)		(0.43)	
iv	2.09***	0.09	-0.20**	-0.04	0.03		
	(2.69)	(0.41)	(-2.47)	(-0.34)	(0.59)		
v	2.12***	0.08	-0.21**	-0.06	0.03	0.03	
	(2.79)	(0.34)	(-2.51)	(-0.50)	(0.64)	(0.14)	
vi	1.95**	0.06	-0.19**	-0.02	0.06	0.10	-0.19
	(2.58)	(0.25)	(-2.25)	(-0.14)	(1.58)	(0.47)	(-1.31)

*** Significant at or above the 0.01 level
** Significant at the 0.05 level
* Significant at the 0.10 level