“Surprise” in Distress Announcements: Evidence from Equity and Bond Markets*

Navneet Arora, Jeffrey R. Bohn, Fanlin Zhu
Moody’s KMV

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Abstract

Some modified structural and reduced-form models of credit risk implicitly assume that the market has less information than managers who declare default on their outstanding debt. As a result the announcement of default or disclosure of information that indicates a firm is in distress comes as a “surprise” to the market. In this paper, we study the extent to which private information is revealed about a firm when it announces information indicating distress. The presence of this private information can be inferred from the extent to which investors can earn abnormal returns on bonds or equities issued by firms announcing distress or default. We analyze how much of the information revealed through the declaration of a credit event is publicly available before a specific announcement of credit difficulties. Using default probabilities supplied by Moody’s KMV (MKMV), known as the Expected Default Frequency™or the EDF™credit measure, we model market expectations regarding the firm’s likelihood of default. We then measure the impact of information revealed through an adverse credit event conditional on this expectation. We find that conditioning on EDF credit measures, only 11% of the distressed firms’ equities and 18% of the distressed bonds (belonging to 25% of the distressed firms) display a significantly negative “surprise” reaction in the sense that the price of these securities drops substantially following the announcement. The vast majority of prices for bonds and equities issued by these distressed firms reflect the firm’s credit deterioration well before announcement of default or distress. Most of these significant negative price reactions tend to occur when a firm declares bankruptcy. We also find that conditioning on lagged equity market returns, the extent of the “surprise” reflected in the corporate bond market shrinks, indicating that equity prices tend to be a leading indicator of a firm’s impending distress. This result, however, can also be due to differences in the samples of bonds and equities, or the lack of liquidity in the market for distressed corporate bonds. Our findings are robust to the choice of time horizon of analysis, and to the choice of publicly available information other than EDF credit measures. Our results have implications for determining the appropriate framework for modeling credit risk.

*Address correspondence to Dr. Jeffrey R. Bohn, Managing Director, Research Group, Moody’s KMV, 1620 Montgomery Street, San Francisco, CA 94111. E-mail: Jeff.Bohn@mkmv.com

1 Introduction

Researchers building and testing credit risk models continue to debate the degree to which market prices reflect sufficient information to predict a firm's default,[1] or does the event of default come as a surprise to investors. If a surprise, the announcement of distress will release significant amounts of inside information about the firm. While markets for corporate bonds and equities may reflect a partial release of information about the financial health of a company, firm managers may still retain information impacting their decision to default on their debt. In this sense, even their decision to not default communicates useful information about a distressed firm.

An interesting question is whether, conditional on the information regarding the fundamentals of a firm, the firm's equity performance, and the firm's decision to not default, the information released upon the announcement of a credit event is significant. As an example, one can compare two prominent defaults: NorthWestern Corp. and Parmalat Finanzaria. Each firm's equity behavior is shown in figures 1(a) and 1(b), respectively. On the one hand, NorthWestern Corp., which declared bankruptcy in September 2003, started seeing its equity steadily losing value almost 18 months before default. On the other hand, Parmalat Finanziaria lost its equity value in a sudden "surprise" event. These two examples reflect very different circumstances. NorthWestern Corp. highlights the ability of the market to anticipate impending distress well before it happens. Parmalat highlights a situation where release of non-public information regarding the actual health of the firm substantially impacts the firm's equity and bond prices at the time of distress. In this case, previously available public information was not indicative of the firm's impending distress. Important questions remain: which example is more representative of the typical distressed firm? Do distressed firms tend to "surprise" the market or is publicly available information generally available to predict a firm's default? Is publicly available information for distressed firms typically inaccurate up until the time distress is clearly communicated? We look to answer these questions empirically.

This overall issue of how well publicly available information foreshadows default materially im-

[1]The use of the term "default" is loose in the sense that firms can indicate distress in a number of ways. Some of the more prominent indicators are formal filing of bankruptcy, non-payment of coupons or principal, distressed exchange of outstanding debt securities, and liquidation. Some researchers define default as non-payment of interest or principal. Other researchers define default only when payments are ninety days past due. Later in the paper, we make a distinction between these different definitions of default and distress. In this section we use "distress" and "default" interchangeably, with both indicating a firm in a state of financial difficulty.

pacts the choice of framework most appropriate for modeling credit risk. The current literature outlining credit-risk-model frameworks can be separated along three broad categories: classic structural models where the event of default is predictable and is defined as a firm's asset value falling below a particular threshold; modified structural models where the event of default is also defined as the firm's asset value falling below a particular threshold, but this event becomes unpredictable due to other informational uncertainty reflected in the model; and finally reduced-form models where default is modeled as an unpredictable Poisson event. Modified structural models and reduced-form models differ in the possibility of "jumping" into default. In the case of the modified structural model, a firm's asset value may jump downward without default occuring. Moreover, the firm may still default regardless of whether the asset value actually jumped downward. In the case of reduced-form models, default can arrive only as a surprise; its linkage with the underlying asset value is never made explicit. If publicly available information tends to signal distress well before a firm defaults, the structural model frameworks will tend to be better candidates for building useful models of credit risk.

The first category of credit risk modeling was introduced by Merton (1974) and Black and Scholes (1973). These structural models typically rest on the premise that the modeler has as much information as the insider, making default a predictable event. Therefore, when a default does occur, there is no significant "surprise" drop in the firm's equity value. Examples of models introduced in the second category are explained in Zhou (1997), Duffie and Lando (2001), and Giesecke and Goldberg (2004). Zhou (1997) adds a jump process into the basic Merton framework. In this modified framework, a firm can default because the firm's asset value has experienced a slow and steady decline or because the firm's asset value suddenly drops or "jumps" into default. Duffie and Lando (2001) pursue a different strategy and assume a restriction on the information set of investors by allowing only periodic and incomplete accessibility to accounting information. This informational gap leads to a framework where a firm may "jump" into default because the information regarding its asset value and/or default threshold is not clear. The result is a default intensity process consistent with the reduced-form modeling approach. Giesecke and Goldberg (2004) introduce uncertainty by assuming the default threshold is unknown and unobservable. Similar to Duffie and Lando (2001), their framework results in a default intensity process. The third category, reduced-form modeling, was developed by Jarrow and Turnbull (1995) and Duffie and Singleton (1999). Hull and White (2000) present detailed explanations of several well-known reduced-form modeling approaches. Many practitioners have gravitated toward this modeling approach given its mathematical tractability. The troubling aspect of this approach is its lack of a link between the default intensity and the underlying firm's asset value and capital structure. The lack of economic structure as an explanation for default makes it more difficult to interpret and diagnose model output.

Proponents of traditional structural modeling methodology argue sufficient market information is publicly available to accurately predict a firm's probability of default. In particular, structural modelers assume the equity market reflects useful information for estimating a firm's probability of default well before distress is more formally disclosed. As a result, the realization of default should not result in the release of new information that causes the stock price to jump. Supporters of modified structural modeling approaches argue that even though the default event occurs in accordance with the traditional structural explanation that a firm's asset value falls below a threshold, this event is not always predictable due to limited information regarding the firm's assets and the firm's default threshold. Reduced-form modelers argue that the event of default is always a "surprise" implying that the realization of default triggers the release of new information. This disclosure causes equity and bond values to "jump".

Jarrow and Protter (2004) argue that reduced-form models are more appropriate in an information theoretic context given that we are unlikely to have complete information about a firm's default point and expected recovery in the event of default. While this statement may be true in a strict, technical sense, equity values still seem to provide substantial information when analyzed in a structural framework. Even if default is a surprise, the degree of surprise should be examined empirically. Jarrow and Protter's claim rests on the premise that a modeler only has as much information as the market, and less information than the insider, making the reduced-form model more realistic. In practice, however, the complete information assumption in structural models is an approximation designed to facilitate a simpler way of capturing the various economic nunances of how a firm operates. A reduced-form model, while not compromising on the informational front, suffers from other weaknesses including lack of clear economic rationale defining the nature of the default process. Given the flexible structure in the functional form for reduced-form models, fitting a narrow collection of credit spreads is straightforward. Unfortunately, this flexibility in functional form may result in a model with strong in-sample fitting properties, but poor out-of-sample predictive ability. The trouble with diagnosing a reduced-form model's goodness of fit and predictive power is that this type of model represents generally atheoretical characterizations of default risk.

The objective of this research is to empirically examine the extent to which latent information is reflected in a default event as measured by the subsequent reaction of stock and bond prices to the event. In order to facilitate this analysis, we use the latent information approach of Acharya (1993). Rather than simply relying on declaration of default as the only signal, this method accounts for the fact that default may not have been a complete surprise. Moreover, this approach facilitates the inclusion of observations where a default has not yet occurred, but information regarding firm distress may have already started leaking into the market. In this way, we account for the possibility that there may be some information reflected in the market regarding the knowledge possessed by firm managers.

The research issues here are two-fold: First, we study whether bond and equity returns jump immediately after the event of default. If there is no extra information in a credit event, we would not expect to see a jump in bond or equity returns. A downward move in bond or equity prices at the time of default would be consistent with Zhou's (1997) framework. Second, to the extent that some firms' asset values do jump at default, we study the value impact of the extra information not captured in bond or equity prices prior to default. For example, a firm's bonds or equities might lose most of their value in a smooth, gradual manner weeks or months prior to default, but still jump down in value near the default date. In this case, a standard diffusion process may still be a reasonable approximation. In contrast, a firm's bond or equities that suddenly fall in value at the time of default may be better modeled with a reduced-form approach. In this case, we focus on whether there is a significant amount of private information that goes into the decision to default once we control for the firm-specific characteristics and the likelihood of defaulting. If we can demonstrate that there is a link between a firm's default and that firm's subsequent stock or bond behavior, conditional on all the available information, then we will have provided evidence supporting the basic assumption of reduced-form models that managers have extra informational advantage over investors.

Jumping to a summary of our primary conclusions, we find that in 88% of the cases of verified default the equity market does not react significantly to an announcement of distress. Interestingly enough, we find similar results in the bond market. In the case of bonds, we find that in 82% of the cases of verified default the bond market does not react significantly to a distress announcement. After conditioning bond returns on lagged equity returns, the percentage of non-reacting bond returns rises to 84%. The fraction of unique firms covered by these non-reacting bonds in the two cases are 75% and 74%, respectively. Conditioning equity returns on lagged bond returns does not change the results for the equity market. This result suggests the equity market tends to lead the bond market in reflecting firm distress. Longstaff, Mithal, and Neis (2004) also find that CDS and equity markets tend to lead bond markets by about a week. While their test was based on a sample of both healthy and unhealthy firms, our result is specific to a sample of financially distressed firms. Our tests also indicate that relative to the market value of equity, the market value of debt is more likely to reflect an element of surprise upon the arrival of default.

The balance of the paper explains our analysis in more detail. In section 2, we describe the latent information methodology and how it is implemented in our tests. In section 3, we describe our data. In section 4, we present our findings and their implications for the ongoing debate among proponents of the different credit-risk modeling approaches. We do some robustness tests in section 5. We conclude in Section 6.

2 Methodology

Our main objective in this paper is to study whether the announcement that a firm faces distress significantly impacts that firm's equity and bond returns. One approach involves testing the significance of the market's reaction to the announcement of distress by calculating a standard deviation adjusted excess return for the firm's equity or bonds and then checking whether this risk-adjusted return is significantly different from zero. Unfortunately, this method faces several difficulties. First, it is not clear how the return behavior of a firm changes as it approaches distress. Second, the arrival of distress is controlled to some extent by the management of the firm. The element of surprise in the market reaction should be considered after accounting for the inferrable "private" information possessed by the firm's management. In other words, the arrival of the news of distress can be treated as a corporate event. Most corporate events are a consequence of some decision process on the part of firm owners or managers. In contrast, the standard methodology for event studies assumes that events are exogenous. When a firm decides to default on its debt or declare bankruptcy, the information privately obtained by the management of the firm can only be partially extracted by the market. Jumps in stock prices or bond prices as a result of announcement of default or bankruptcy depends on market inference of the latent information underlying the decision process (Acharya (1988), Acharya (1993)). Inference of latent information depends on the market's prior information. This prior information likely differs across two different firms making the same announcement. For example, a firm with extremely high leverage and poor profitability declaring bankruptcy will likely have less latent information compared to a less leveraged firm declaring bankruptcy.

The latent variable model suggested in Acharya (1988) accounts for market inference and computes the inferred value of information underlying an event announcement process. The model measures the expected abnormal return to an event, conditional on firm-specific pre-event information. Further, it uses data over the event and the non-event periods. Pre-event information can include firm-specific accounting variables and past stock-returns.

2.1 Latent Information Approach

An advantage of using the latent information methodology is that a firm's decision to default is not likely to be a complete surprise to the market. Much of the information available to the manager is also available to the market via financial statements and commentary from analysts following the firm. The manager also possesses information not directly available to the market. The relevant question concerns the extent to which the private information stays private over time and the extent to which public information effectively signals firm distress well in advance of explicit announcement of distress. The latent information method allows us to model the nature of the probability expectations that a default will occur. This approach allows for the possibility that default may be due to both public and private information and establishes whether the private component is significant.

Our conditional event study treats default as an endogenous event. We formulate a decision process for each event and measure the impact of announcements in relation to this process. In the case of default, we denote our decision process by $Default_{it}$. This variable corresponds to a manager's view whether firm i should default at time t. As long as $Default_{it}$ maintains a certain level, the firm will avoid default. When $Default_{it}$ falls below this level, default will occur. Econometrically, this relationship can be expressed as:

$$Default_{it} = \theta' X_{it-1} + \Psi_{it} \tag{1}$$

Here $\theta' X_{it-1}$ represents investors' expectation regarding the firm's possibility of default, conditional on firm-specific information contained in the vector X_{it-1}. Ψ_{it} represents the manager's inside information. While the market cannot observe the latent information contained in Ψ_{it}, it can observe whether default occurs. Assume that the firm will not default as long as $Default_{it}$ exceeds zero. When $Default_{it}$ falls below zero, default occurs. We can then define an indicator variable I_{dit} that will equal one when a default occurs for firm i at time t.

$$\begin{aligned} I_{dit} &= 0 \text{ whenever } \theta'\mathrm{X_{it-1}} + \Psi_{\mathrm{it}} > 0 \\ &= 1 \text{ otherwise} \end{aligned} \tag{2}$$

In this framework, the market can infer something about the value of Ψ_{it}, the manager's inside information, depending on whether the firm defaults. Even the observation that default does not occur provides some information about the value of Ψ_{it}, i.e., it must be the case that $\theta' X_{it-1} + \Psi_{it} > 0$.

Given this managerial decision framework, we now relate this process to abnormal returns observed when default occurs. More specifically, we are interested in understanding abnormal returns experienced by firm i at time t, denoted by ϵ_{it}. Following Acharya (1993), we can write this as:

$$\epsilon_{it} = \pi_e \Psi_{it} + \eta_{equity,it} \tag{3}$$

where $\eta_{equity,it}$ is independent of the event happening, i.e. $E\left[\eta_{equity,it} | I_{dit}\right] = 0$ regardless of whether I_{dit} equals zero or one. The abnormal return is obtained from the market model:

$$R_{equity,it} = a_{e,i} + b_{e,i} R_{mt} + \epsilon_{equity,it}$$

where $R_{equity,it}$ is the return on the stock, and R_{mt} is the return on the market portfolio. When a firm does not default, then the market's expectation of ϵ_{it} is

$$E\left[\epsilon_{equity,it}|I_{dit}=0,W_{it}\right] \tag{4}$$

Substituting in our specified relationship from equations (2) and (3), we can rewrite this expectation as:

$$\pi_e E\left[\Psi_{it}|X_{it-1},\Psi_{it}>-\theta' X_{it-1}\right] \tag{5}$$

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In this equation, a positive and significant π_e can be interpreted as the market's negative reaction to the announcement of distress. Similarly, a negative and significant π_e can be interpreted as a positive reaction of the market to the announcement of distress. If π_e is not significantly different from zero, we can infer that conditional on publicly available information, no significant information was released at the time of the firm announcing distress and therefore the market did not react. As described in Section 4, this methodology can be easily adapted to study the significance of reaction of bonds to the announcement of distress.

2.2 Estimation

We estimate the model with a simple, consistent two-stage procedure (Acharya (1993)). In the first stage, the probability of the event, $\Phi\left(\psi_{it}\right)$, can be estimated using a probit model with I_{dit} as the dependent variable and X_{it} as the independent variable. This probit model assumes that Ψ_{it} $\forall$ i, and t, are independent. In the second stage, the model is estimated using a simple OLS, with the coefficient θ in X_{it} replaced by their maximum likelihood estimates. Thus the estimate is basically a combination of a probit and an ordinary least square regression.

3 Data

A comprehensive sample of defaulted firms is central to answering the empirical questions raised in this paper. The default data we use are provided by Moody's KMV, a market leader in credit risk modeling. This dataset captures various forms of financial distress– namely defaults (defined as non-payment of principal or interest), bankruptcies, liquidation, and distressed-exchange– together with the source that announced this news and the date of announcement. Moody's KMV has employed full-time staff to collect these data since its inception in 1989. Weekly equity data were collected from Compustat, while the proxy for market return data- S&P 500- was collected from Yahoo. Daily equity data were provided by Bloomberg. Bond data were provided by EJV-Reuters, a premier provider of bond data that is well regarded for its wide coverage. For firm specific information available to the market, we used default probabilities provided by Moody's KMV. For our robustness analysis, we used accounting variables and market capitalization data provided by Compustat. Our study covers firms that defaulted between 1999 and 2004.

Table 1 shows the distribution of firms across different distress events. Most distress events are either bankruptcies or defaults. We have equity data on a subset of these firms. We eliminated 20% of the sample due to the lack of usable equity data.

4 Results

4.1 Qualitative Evidence from Data

We first explore the nature of the equity market's reaction to default. Figure 2(a) shows the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles of equity return behavior 44 days prior to bankruptcy until 22 days post that bankruptcy. Figure 2(b) shows similar data for 44 days prior to default until 22 days after default. Figures 3(a) shows the 10^{th}, 25^{th},50^{th}, 75^{th}, and 90^{th} percentiles of EDF ™behavior 44 days prior to bankruptcy and 22 days post that bankruptcy. Figure 3(b) shows similar data for default. In both cases, the median equity returns are fairly smooth and the median firm does not exhibit any significant jump in equity returns. These pictures, however, pool data cross-sectionally and across time raising concerns that individual firm behavior is masked.

As another check, we consider a simple criterion for determining equity price jumps. We define a jump as equity returns less than or equal to negative 20% in any week over a particular time horizon. In other words, if

$$\rho_{equity,it} < -0.20 \tag{10a}$$

then we define this price move as a jump.

Table 2(a) examines the distribution of jumps by this criterion across distress types for various horizons. We observe more jumps by this criterion: almost 50% of the firms exhibit a jump at some point. This criterion, however, may not be as useful in evaluating the dynamics of the underlying decision processes. Most equities lose considerable value well before default is communicated to the market. As the firm nears the time of announcing default, a small move in equity price can still exceed 20%. A \$100 stock is less likely to fall to \$80 over a week, than for a \$1 stock to fall to \$0.80 since the latter is likely to be more volatile. In the case where an equity traded previously in the \$100 range, drifted to the \$1 range over several months, and then fell to \$0.80 a week before default would still not be well modeled with a jump-based framework despite the final price move that may appear to be a jump in isolation. This rigid criterion for defining jumps admits many "uninformative" price moves.

As another check, we defined a jump as an equity return greater than three standard deviations of equity returns over a particular time horizon. We used the following procedure: First, eliminate the highest three positive and highest three negative returns from the sample. Then compute $\sigma_{equity,i}$ as

$$\sigma_{equity,i} = \sqrt{\frac{\sum_{i=t-H}^{t} \rho_{equity,it}^{2}}{H}} \tag{10b}$$

A jump is defined as any negative return which is more than three times the standard deviation of equity returns in its absolute value:

$$\rho_{equity,it} < -3\sigma_{equity,i} \tag{10c}$$

While this method is a fairly coarse way to measure jumps, we expect it will identify all outlier returns. Unfortunately, this method will not discriminate among the causes of a jump. In particular, this method does not distinguish equity market liquidity shocks from the release of new information regarding a firm. To the extent liquidity shocks are reflected in the data, this method will overestimate the number of jumps arising from new information. Since our objective in this section is only qualitative examination of the data, we do not probe this issue any further.

Table 2(b) shows the distribution of jumps that we observed in our data by this standard-deviation-based measure. Despite the coarseness of this criterion, only 233 of 1271 distressed firms with available equity data exhibit a jump in their equity prices within a week before or after default. In all, 894 firms experience a week over which their negative returns exceed 3 standard deviations within 6 months of default. Of these, 388 were not within a month of default, implying that the information was released before the actual event of default. Therefore, it would appear from this test that for most firms, the actual event of default did not result in a substantial release of information, as indicated by a jump in their equity returns.

Two comments are in order here. First, in the strictest sense, one ought to look for jumps close to the actual date of the distress announcement. We present jumps by both criteria within one day before and after the announcement in tables 2(a) and 2(b). Many firms do not have equity data on these dates, but among the ones that do, we find that around 40% exhibit jumps by either criteria. Second, as mentioned above, while we may capture "jumps" given the above criteria, these "jumps" may not be informative. That is, many of these "jumps" are likely not reflective of a credit-related event. These price moves may be a result of noise or illiquidity. consider the example of a firm whose equity return volatility has a noise component equal to 10% on a weekly basis. If this firm's equity return drops by 15% during the week of it announcing distress, this move may not be as significant as that of a firm whose equity return drops by 10% in the week of default, but the noise component of its equity return volatility is only 1% per week. Our objective is to segregate the latter cases from the former and thereby discern "informative" jumps. A better way to segregate informative "jumps" is to use the latent information technology described in section 3.

4.2 Evidence from Latent Information Methodology

We first establish a relationship between the MKMV EDF credit measures and the frequency of default using a probit regression specified as:

$$I_{dit} = \alpha_i + \beta_i ln\left(EDF_{it-1}\right) + u_{it} \tag{11}$$

The results of the regression based on daily returns data are shown in table 3. As expected, the default probabilities seem to be significant indicators of realized defaults, judging by the positive coefficient β_i on $Ln(EDF)$. Table 4(a) shows that, on a median basis, the coefficient on the latent information in a default event is distributed around 0, with the median only marginally positive. The firms in the largest 10% of the sample by magnitude of π_e are the ones that are statistically significant. After studying the distribution of π_e as in table 4(b), one finds that there are 110 firms for which the coefficient π_e is positive and significant and 52 cases in which the coefficient π_e is negative and significant. These results indicate that out of a sample of 980, about 11% of the firms seem to reveal "surprise" negative information around the event of default while for the rest of the 89%, the information was fairly insignificant or significant in a counter-intuitive direction i.e. announcement of distress resulted in a significantly positive return.

4.2.1 Reaction of Equity Markets to Distress Announcements

Figure 4(a) shows the median return for significant π_es– both positive and negative. During the week of default, the significantly positive π_es firms had a median return of almost -60%. The firms with significantly negative π_es had a median return of almost 40%.

We next wanted to understand if the nature of the distress event had something to do with the amount of "surprise" stored in the distress event. To this end, we looked at the distribution of the significant π_es across distress events in table 5(a). We find that most of the positive π_es come from bankruptcy announcements. A possible explanation for this result concerns the difference between expectation and realization. The market may have expected a default, i.e. non-payment of principal or interest, but not a bankruptcy with its accompanying costs of dealing with bankruptcy court proceedings. Moreover, bankruptcy is more likely to result in complete loss of equity value whereas default can be overcome in terms of renewed cash flow prospects for the firm. As a consequence, some bankruptcy events may be followed by a further negative shock to equity value. The evidence that equity markets anticipate some distress for firms that went bankrupt can be seen in figure 3(a) where most firms had MKMV default probabilities of 20% (a sign of a substantially distressed firm according to the MKMV EDF measure; EDF values greater than 2% indicate distress.) Only the lowest 10 percentile of the sample had EDF values less than 20%; even for this sample, the EDF credit measures are above 10% and climb to 20% about 20 days before bankruptcy is announced. In comparison, figure 3(b) shows that for default cases, the 25^{th} and 10^{th} percentile EDF measures fall below 20%, although the 25^{th} percentile arrives at 20% about a week before default.

Next, we completed an aggregate panel regression where we pooled the data cross-sectionally by bucketing them across the four distress types: bankruptcy, default, distressed exchange, and liquidation. This approach generates distress-event specific π_es instead of firm-specific π_es. The results are presented in table 5(b). In aggregate, only the bankruptcy event announcements lead to a "surprise" reaction from the equity markets, while the others do not lead to any significant reaction at all.

We also examined the characteristics of firms that exhibit significant reactions upon announcement of distress. The three main characteristics considered are: size (as measured by book asset value), asset volatility (provided by MKMV's Vasicek-Kealhofer (VK) Model[2]), and leverage (as measured by total adjusted liabilities as a fraction of book asset value). In table 5(c), we see that firms that exhibit a significant negative reaction to distress announcement (i.e. positive π_e) tend to be higher leveraged with lower asset volatility; however, the differences are marginal.

4.2.2 Reaction of Bond Markets to Distress Announcements

In the above section, we analyzed the reaction of equity markets to arrival of a distress event. Investors in corporate bonds are also focused on the possibility of firm distress. If corporate bond markets are efficient then the extent of reaction exhibited by bonds should be comparable to that of equity markets. The market for high-yield bonds is fairly illiquid. Most firms that default tend to be issuers of high-yield bonds. Therefore, we expected that the high-yield bond price data will tend to reflect more sudden movements in price than reflected in equity prices in reaction to announcements of firm distress.

In this framework, we can relate the managerial decision framework to abnormal returns observed for bonds when default occurs. More specifically, we are interested in understanding abnormal returns experienced by firm i at time t, denoted by $\epsilon_{bond,it}$. Following Acharya (1993), we can write this as:

$$\epsilon_{bond,it} = \pi_b \Psi_{it} + \eta_{bond,it} \tag{12}$$

where $\eta_{equity,it}$ is independent of the event happening, i.e. $E\left[\eta_{equity,it}|I_{dit}\right] = 0$ regardless of

[2]See the appendix for more details on the VK model.

whether I_{dit} equals zero or one. The abnormal return is obtained from the market model:

$$R_{bond,it} = a_{b,i} + b_{b,i}R_{mt} + \epsilon_{bond,it}$$

where $R_{bond,it}$ is the return on the bond, and R_{mt} is the return on the market portfolio. When a firm does not default, then the market's expectation of $\epsilon_{bond,it}$ is

$$E\left[\epsilon_{bond,it}|I_{dit} = 0, W_{it}\right] \tag{13}$$

Substituting in our specified relationship from equations (2) and (12), we can rewrite this expectation as:

$$\pi_b E\left[\Psi_{it}|X_{it-1}, \Psi_{it} > -\theta' X_{it-1}\right] \tag{14}$$

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In this equation, a positive and significant π_b can be interpreted as the market's negative reaction to the announcement of distress. Similarly, a negative and significant π_b can be interpreted as a positive reaction of the market to the announcement of distress. If π_b is not significantly different from zero, we can infer that conditional on publicly available information, no significant information was released at the time of the firm announcing distress and therefore the bond market did not react to the news.

Table 9 shows the distribution of π_bs when the bond returns are regressed upon the market index and firm-specific latent information. We find that 150 of the 831 bonds, or about 18% of our sample, have positive and significant π_b. This number is slightly larger than the percentage of positive and significant π_e found in the equity data indicating that there is some evidence that bonds are more susceptible to a "surprise" reaction to the latent information released upon the news of default.

Further, adding lagged information from the equity market to this regression, we find that the number of bonds that have a positive and significant π_b drops from 150 to 132. This modification reduces the fraction of surprise drops in value to 15% indicating that the element of surprise drops if information from equity markets is used. We then explored the extent to which the equity market provides informational incremental to the information reflected in the bond market. We also look at the extent to which the bond market provides incremental information to the information reflected in the equity market. To this end, we conducted the following regression:

$$\rho_{equity,it} = \alpha_e + \beta_{1e}\rho_{bond,it-1} + \beta_{2e}\rho_{bond,it-2} + \epsilon_{eit} \tag{15}$$

$$\rho_{bond,it} = \alpha_b + \beta_{1b}\rho_{equity,it-1} + \beta_{2b}\rho_{equity,it-2} + \epsilon_{bit}$$

The results are presented in table 10. Judging by the positive and statistically significant coefficients β_{1b} and β_{2b}, it does appear that lagged equity returns add incremental information for explaining bond returns. The reverse, however, is not true as demonstrated by statistically insignificant coefficients β_{1e} and β_{2e}. This evidence corresponds with the fact that the number of bonds demonstrating a "surprise" reaction drops when lagged equity information is used. This finding is consistent with Longstaff, Mithal, and Neis (2004) who find evidence that equity and CDS markets tend to lead bond markets. While their study was based on a sample of both healthy and unhealthy firms, their similar findings support our conclusions.

4.3 An Alternative Definition of Distress Events

We appreciate that distress can be defined in many ways. Our data reflect publicly announced distress events; however, an investor or a lender may be more focused on the event of a substantial fall in bond price regardless of whether distress was formally announced. In this sense, distress should be defined in terms of bond prices falling to a particular level. Therefore, as an extension to our testing methodology, we altered our dataset to define the realized dates of distress as the time when the bond prices fell below a particular threshold. Based on discussions with market participants, we defined distress as the bond price falling more than 20%. We then repeated our experiments with this revised list of distressed names. The results are presented in table 11 and are shown for two sub-samples:

(a) *firms that were formally announced in distress*: For these firms, the event date was chosen as the formal announcement of distress, or a sudden decline in bond price, whichever came first. The restriction of the sub-sample to formally distressed firms assures us that the firms chosen were indeed in distress, and therefore the equity markets response was more likely dictated by an actual credit event.

(b) *all firms where bonds declined in price by 20% over a week*: For these firms, the event date was chosen as the formal announcement of distress, or a sudden decline in bond price, whichever came first. However, unlike in (a), our sample was not restricted to formally distressed firms. That is, firms defined as distressed may not have formally announced distress. Hence, in many cases, the event may have been caused by lack of liquidity rather than an actual credit event. Therefore, we risk an over-estimated number of events in this sample.

In table 11, we find that under the assumption outlined in (a), equities of 35% of the firms have a surprise reaction to the distress event, while based on the assumption outlined in (b), equities of 58% of the firms have a surprise reaction to distress events.

The results of this test must be interpreted with two caveats. First, these results are based on a small sample size of firms that had bonds and exhibited characteristics of distress based on the descriptions in (a) or (b). For most of the distressed firms in our sample, we do not have regular time-series data of traded debt. Second, upon arrival of these credit events, the equity has already lost most of its value. At very low equity prices, a surprise decline in percentage value of equity is perhaps due to an increased volatility of its returns. To demonstrate this behavior, we plot the 25^{th}, 50^{th} and 75^{th} percentiles of MKMV EDF measures for these firms in figure 5. The median firm reaches a default probability of 20%, which is interpreted as a significantly high default probability usually associated with low equity values. Ignoring these caveats, it does seem that re-defining the credit event based on the market value of debt seems to increase the element of surprise in the reaction displayed by equity markets.

5 Robustness of Results

In the previous section, we looked at the results of our tests under specific assumptions regarding the event-window horizon and data frequency. We also assumed that default probability estimates are easily accessible and represent a complete set of control information, i.e. X_t in equation (1). In this section, we revisit our tests by relaxing those assumptions to verify the robustness of our results.

To determine whether the results are dependent on a particular event-window horizon, we repeat the above regression by choosing two different time windows: a daily window from 44 days before default to the day of default and a weekly window from 26 weeks before default to 13 weeks after default. The results are presented in tables 6, 7, and 8 respectively. These results are similar to what we found above. In table 6, we repeat our probit regression using a time horizon of 44 days before default to the date of default. Once again, we find a positive and significant coefficient on

$ln(EDF)$ indicating that the default probabilities generated by MKMV are significant predictors of distress. In Table 7(a), we present the π_e distribution for the OLS regression as in equation (8) for this new time horizon. In table 7(b), we show the π_e distribution in terms of signs and significance. For this time horizon, we find that 111 out of 980 firms, or about 11 % of the firms have a positive and significant π_e, indicating that once again, about 89% of the firms did not have a significant downward post-distress announcement reaction.

One concern we had related to the noisiness of daily returns data since many of these firms do not trade on a daily basis. To evaluate the impact of the return horizon, we looked at the weekly returns of these firms, and expanded the time horizon to 26 weeks before distress and 13 weeks after distress. The results are presented in table 8(a) and 8(b). Table 8(a) shows the π_e distribution. We find in table 8(b) that for weekly data and a longer horizon before and after default, 142 out of 1180, or about 12 % firms had a positive and significant π_e. That is, 88% of the sample did not react significantly to the news of distress. Figure 4(b) shows the median return for the significant π_es– both positive and negative in the week of default. During the week of default, the significantly positive π_e firms had a median return of approximately minus 60%. The firms with significantly negative π_es had a median return of almost 60%.

Another issue to consider concerns the extent to which the MKMV EDF measure should be treated as a private signal since this measure is available only to paying clients. While the MKMV EDF measure reflects extensive filtering efforts to ensure the use of quality data and an extended structural model developed to be useful in practice, less sophisticated implementations of a structural model may extract some signal. We consider a simple implementation as follows: In equation (1), we used the following structural variables as proxy for the vector X- Market Capitalization to (Market Capitalization + Total Liabilities) ratio, book asset value, equity volatility, earnings before depreciation, tax and amortization (EBITDA) to common book equity ratio.

The probit regression is presented in table 12(a). Table 12(b) shows the significance and signs of π_e from this regression. We find results approximately similar to what we reported in the previous section. In summary, the MKMV EDF measure or the information reflected in the measure appears to be a public signal. In most cases, this information leaks out prior to the announcement of distress.

6 Conclusion

In this paper, we empirically examined the extent of "surprise" reflected in the equity and bond prices of firms that announce events such as bankruptcy, default, distressed exchange, and liquidation. These events indicate the firm is distressed. The results of this study have implications choosing the best approach for implementing credit risk models. A surprise reaction to the announcement of distress that leads to a jump in bond and equity prices corresponds with the assumption in the reduced-form modeling framework that defaults come as a surprise. A lack of reaction in prices corresponds with the assumption in the traditional structural modeling framework that equity market information can be transformed into measures that are indicators of which firms are likely to become distressed. Our empirical findings indicate that equities of only 11% of distressed firms in this sample display a significant negative reaction in the week following the announcement of a distress event. In contrast, bonds of about 18% of the firms display a significant negative reaction during the same period. We also find that the majority of these firms that display a significant negative reaction are associated with bankruptcy announcements. Consistent with this result, we find that bond returns carry some lagged information from equity markets, indicating that bond returns tend to lag equity returns. That is, conditional on lagged equity information, the number of companies for which the bonds display a surprise reaction falls.

Another interesting finding is that about 5% of the firms in our sample display a positive "surprise" upon announcement of distress. Most of these positive reactions are associated with default. This could be because a default is a milder event compared to bankruptcy. In these cases, the realization of default may be associated with a strategy on the part of the equity holders to capture more of the liquidation value of the firm. As a consequence, the announcement of default might be viewed as positive information by the equity market. However, this conjecture needs to be tested. In general, we do not find any prominent difference in the firm characteristics based on their reactions except that firms with maximum negative surprise tend to be slightly higher leveraged and lower asset volatility firms. Our findings are robust to the choice of horizon chosen for the event-window as well as to the choice of variables available to proxy for the publicly available information. These findings should be considered when choosing a modeling framework for evaluating default risk.

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7 Appendix A: MKMV Default Probabilities

MKMV provides a term-structure of physical default risk probabilities using the VK model. This model treats equity as a perpetual down-and-out option on the underlying assets of a firm. This model assumes five different types of liabilities: short-term liabilities, long-term liabilities, convertible debt, preferred equity and common equity. MKMV uses the option-pricing equations derived in the VK framework to derive a firms market value of assets and its associated asset volatility. The default point term-structure (i.e. the default barrier at different points in time in the future) is determined empirically. MKMV combines market asset value, asset volatility, and the default point term-structure to calculate a Distance-to-default (DD) term-structure. This term-structure is translated to a physical default probability using an empirical mapping between DD and historical default data.

$$DD_T = \frac{log\left[\frac{A}{X_T}\right] + \left(\mu - \frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}} \tag{16}$$

X_T in VK model has a slightly different interpretation than in Merton model. In the analytical stage of the model, if asset value A falls below X_T at any point in time, then the firm stands in default. VK model empirically estimates a term-struture of this default barrier to come up with a DD term structure that could be mapped to a default-probability term-structure, hence the subscript T for default barrier X. The basic methodology is discussed in Crosbie and Bohn (2003), Kealhofer (2003a), and Vasicek (1984). The model departs from the traditional structural model in many ways. First, it treats the firm as a perpetual entity that is continuously borrowing and retiring debt. Second, by treating different classes of liabilities, it is able to capture some nuances of the capital structure. Third, it calculates its interim asset volatility by generating asset returns through a de-levering of equity returns. This is different from the popular approaches that compute equity volatility and then de-lever it to compute the asset volatility. Fourth, it generates the final asset volatility by taking a weighted average of the interim asset volatility as computed above together with a modeled volatility estimated on comparable firms. This step helps filter out noise generated in equity data series. Fifth, the DD term structure and the subsequent default probability term-structure result in a downward slope for riskier firms and an upward slope for safer firms. This pattern is consistent with the empirical credit-migration patterns found in the data. These modifications address many of the concerns raised by Eom, Helwege and Huang (2003) that generate over-estimates of spreads for riskier bonds and under-estimates of spreads for safer bonds. The default probability generated by the MKMVs implementation of the VK model is called an Expected Default Frequency™or EDF™.

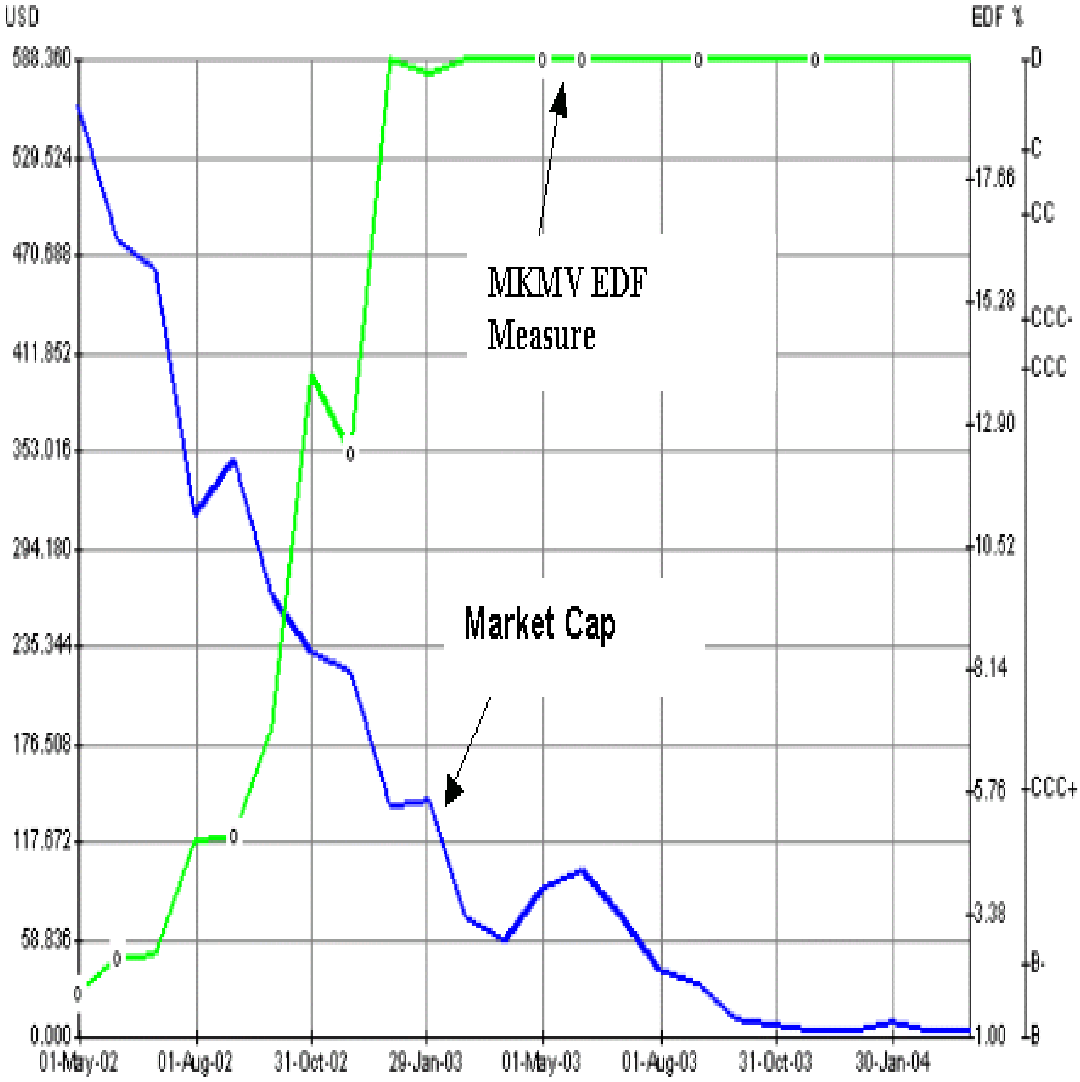

Figure 1(a): Equity Behavior for NorthWestern Corp. over time till bankruptcy.

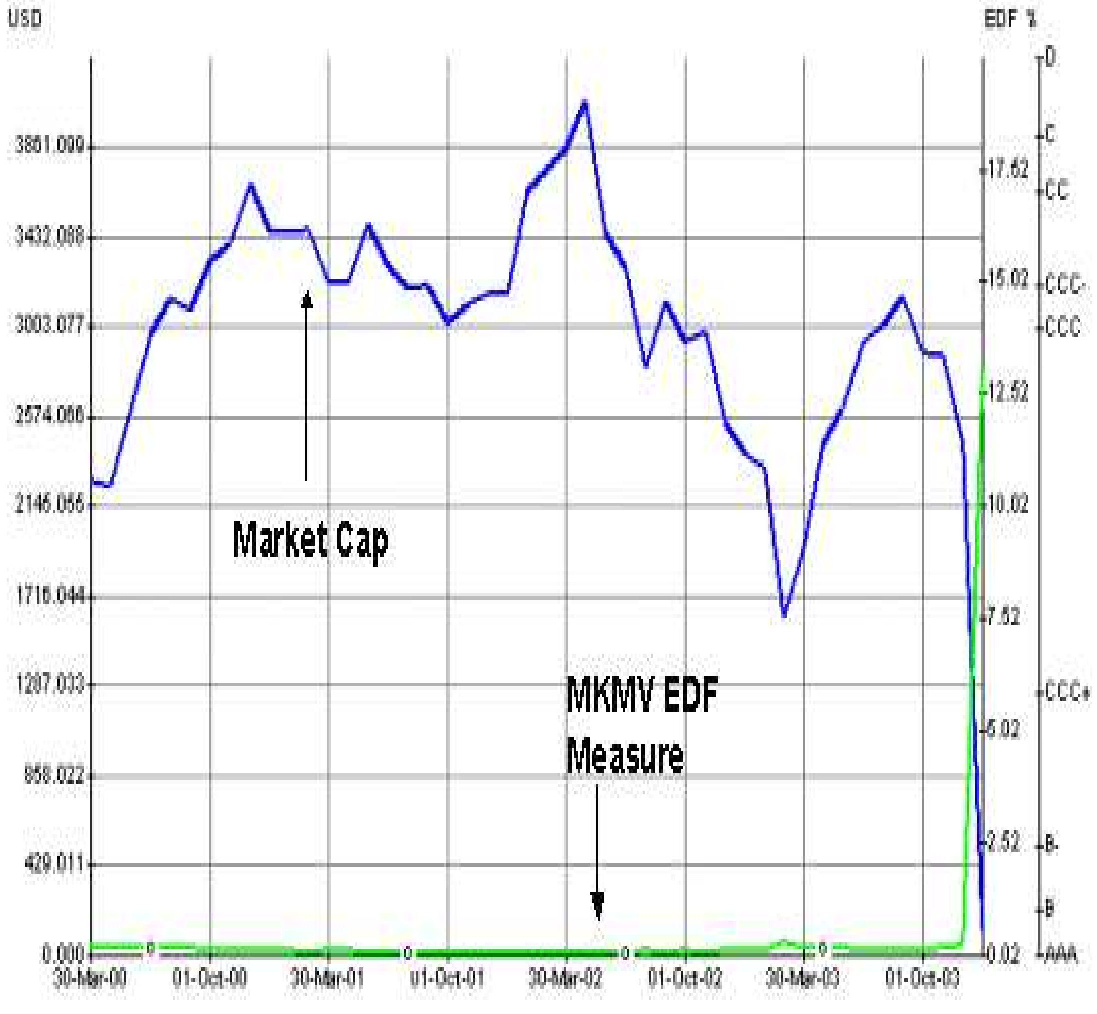

Figure 2(a): Equity Behavior for Parmalat Finanziaria over time till bankruptcy.

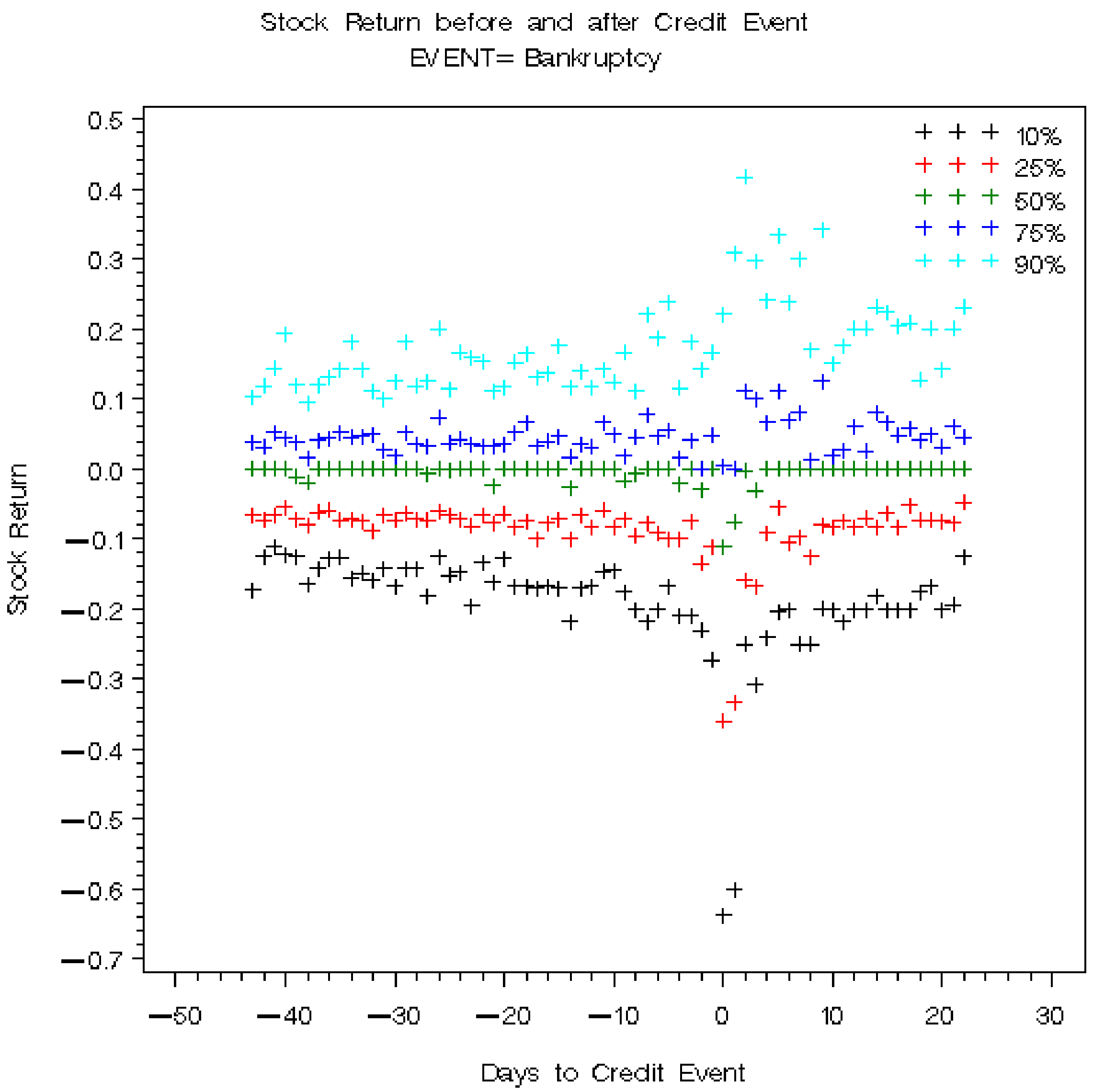

Figure 2(a): 10^{th}, 25^{th}, 50^{th}, 75^{th} and 99^{th} percentiles of returns on stocks prior to and post-bankruptcy.

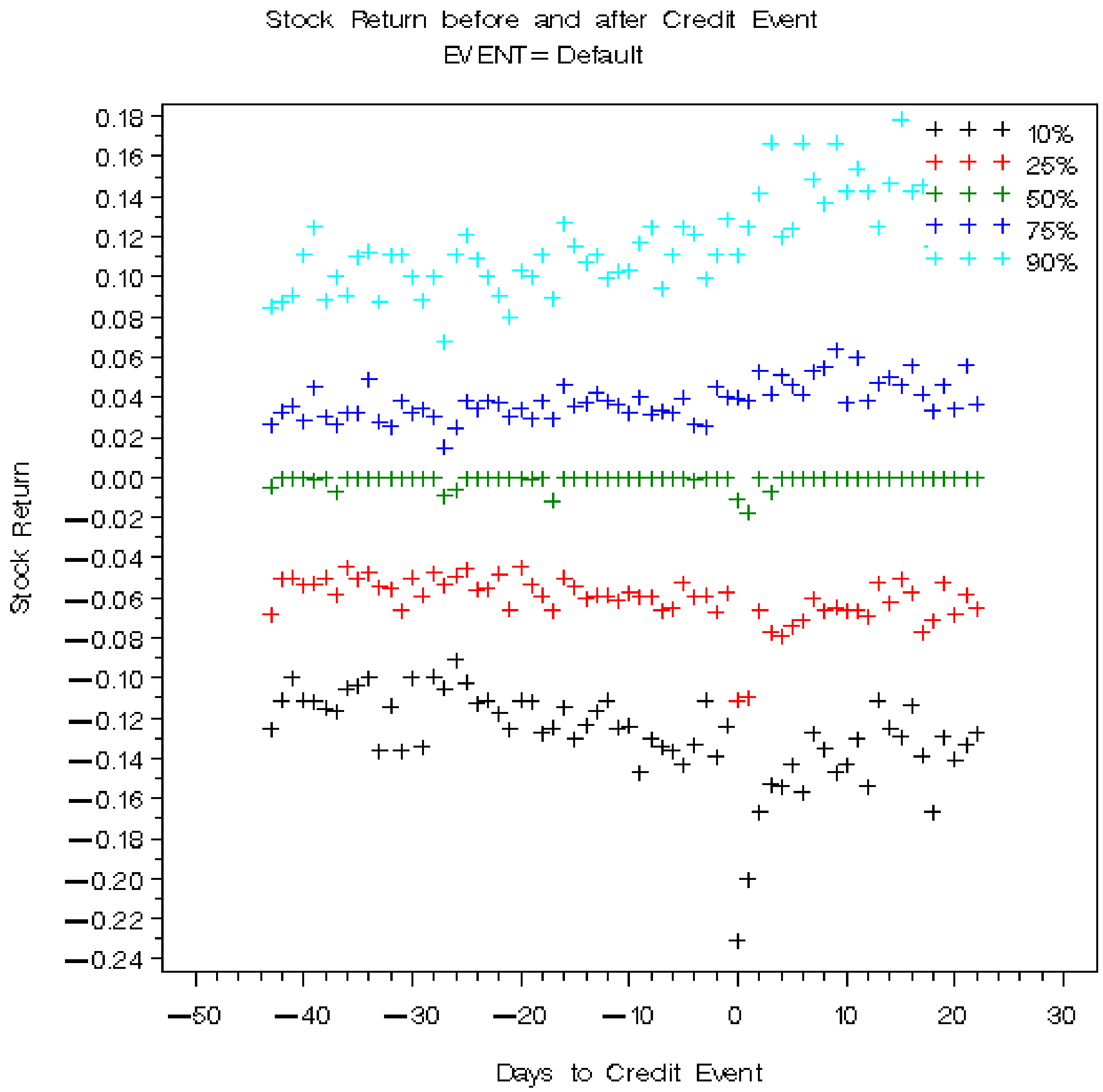

Figure 2(b): 10^{th}, 25^{th}, 50^{th}, 75^{th} and 99^{th} percentiles of returns on stocks prior to and post-default.

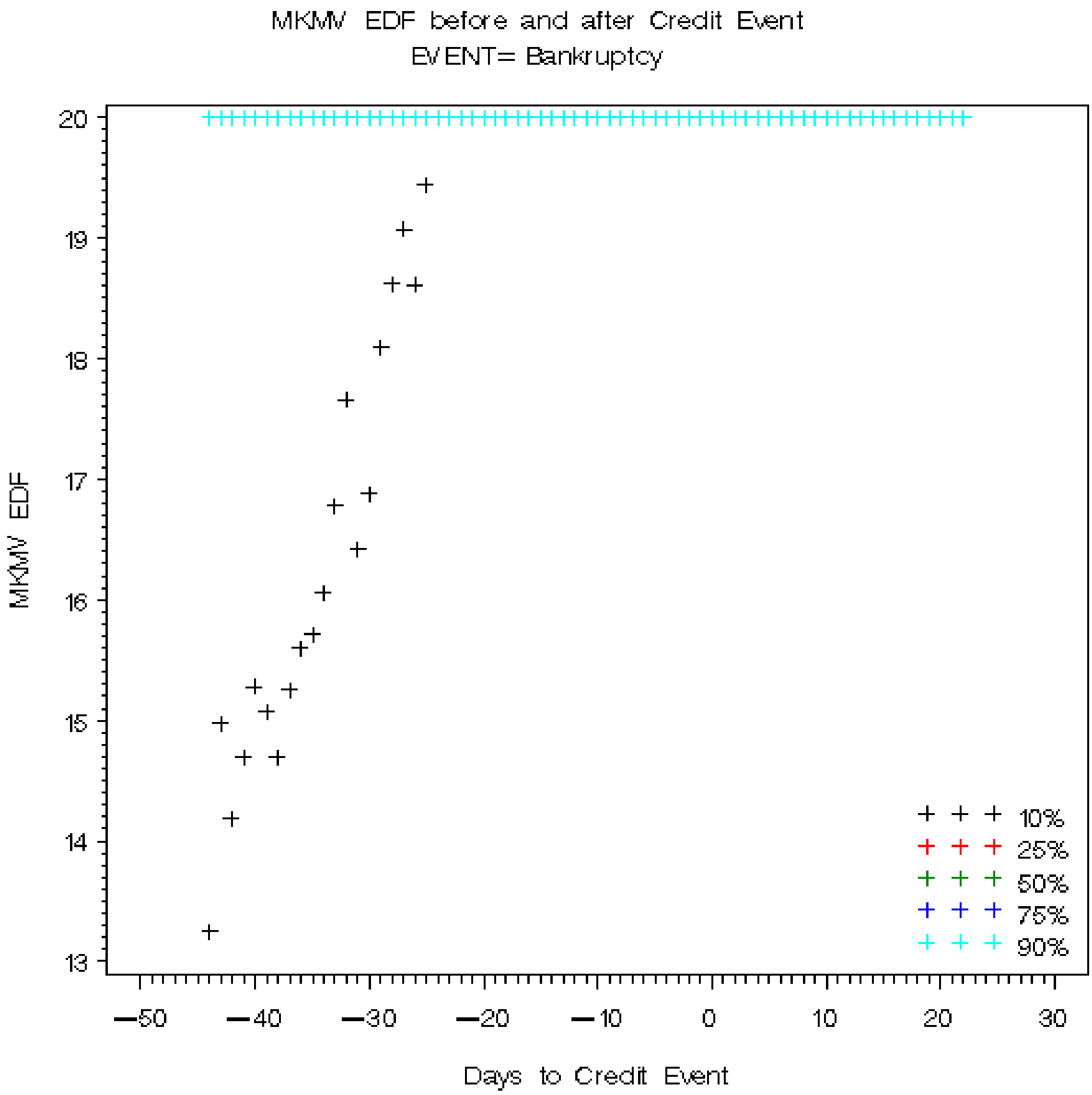

Figure 3(a): 10^{th}, 25^{th}, 50^{th}, 75^{th} and 99^{th} percentiles of EDF values of bankrupt companies prior to and post-bankruptcy.

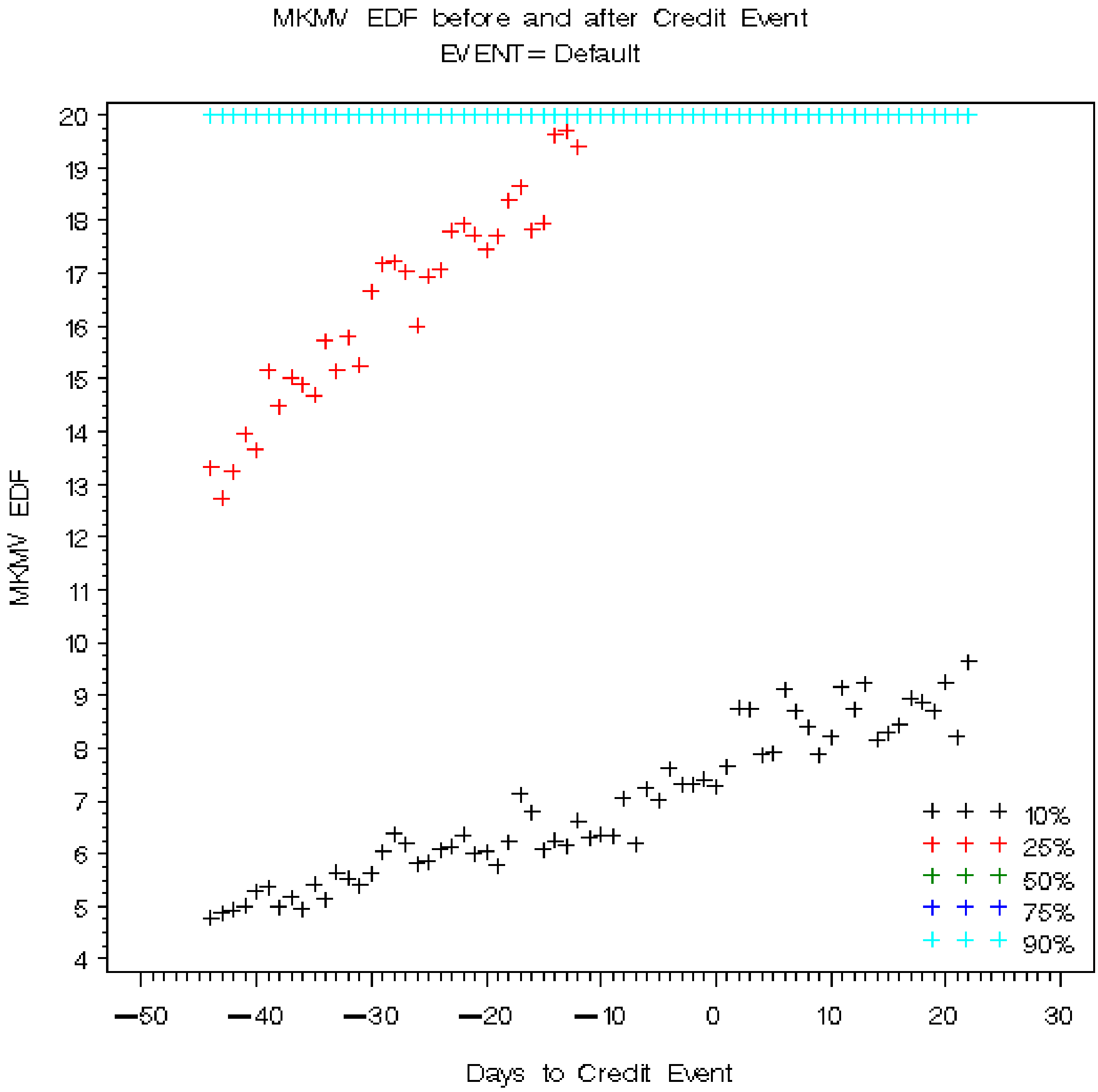

Figure 3(b): 10^{th}, 25^{th}, 50^{th}, 75^{th} and 99^{th} percentiles of EDF values of defaulted companies prior to and post-default.

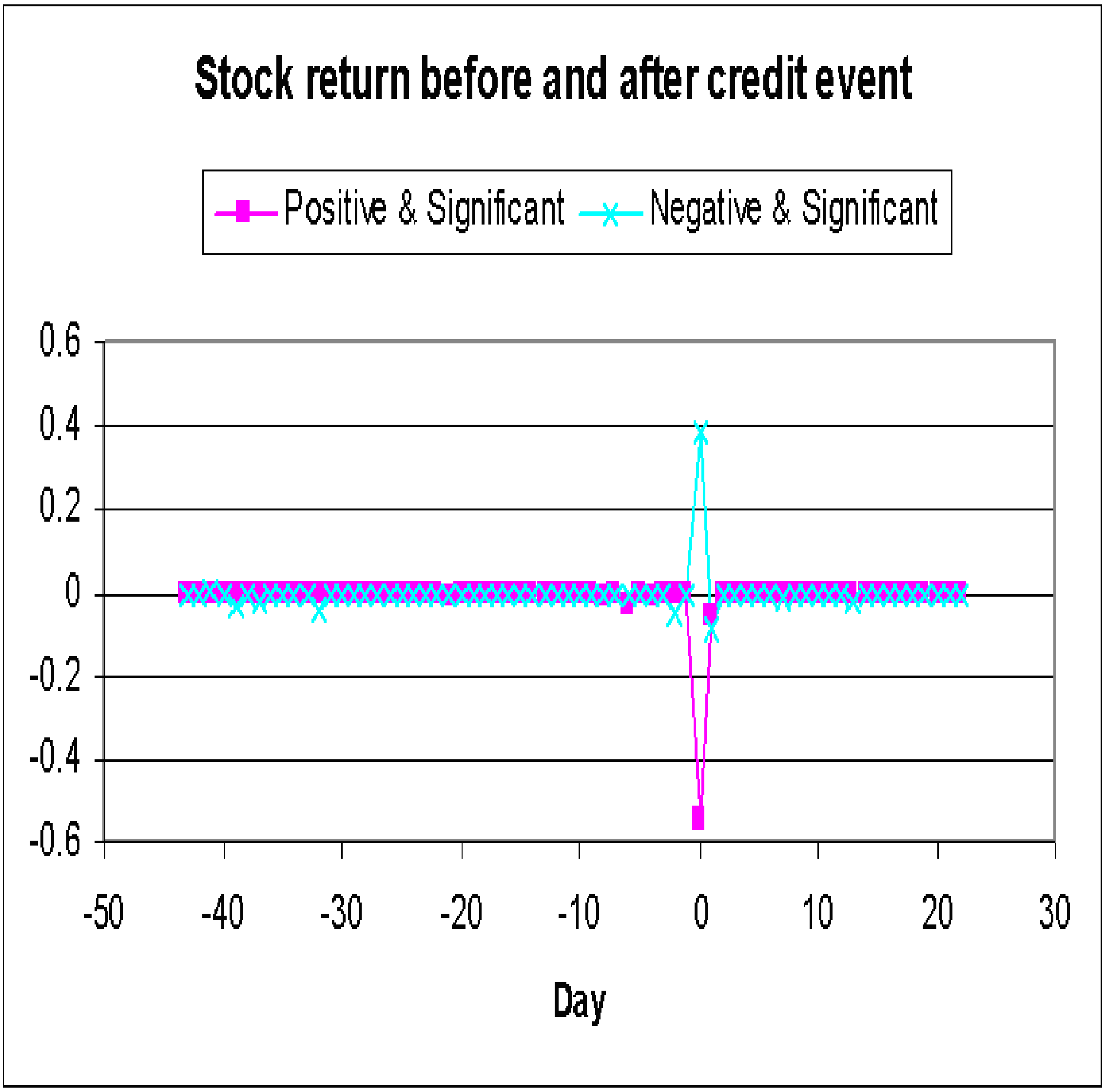

Figure 4(a): Median returns on stocks prior to and post-distress for firms with significant (positive and negative) π_e using daily data.

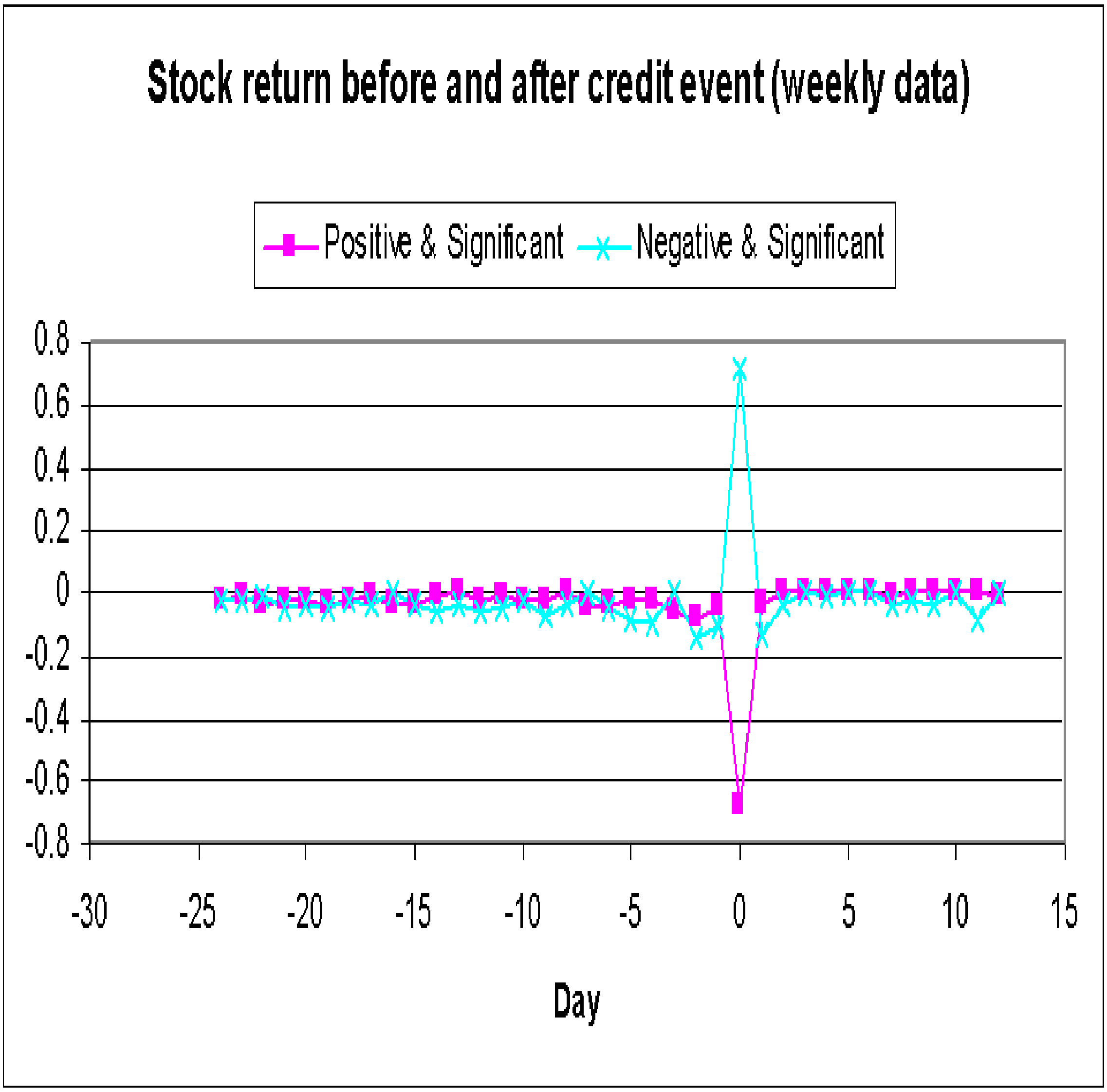

Figure 4(b): Median returns on stocks prior to and post-distress for firms with significant (positive and negative) π_e using weekly data.

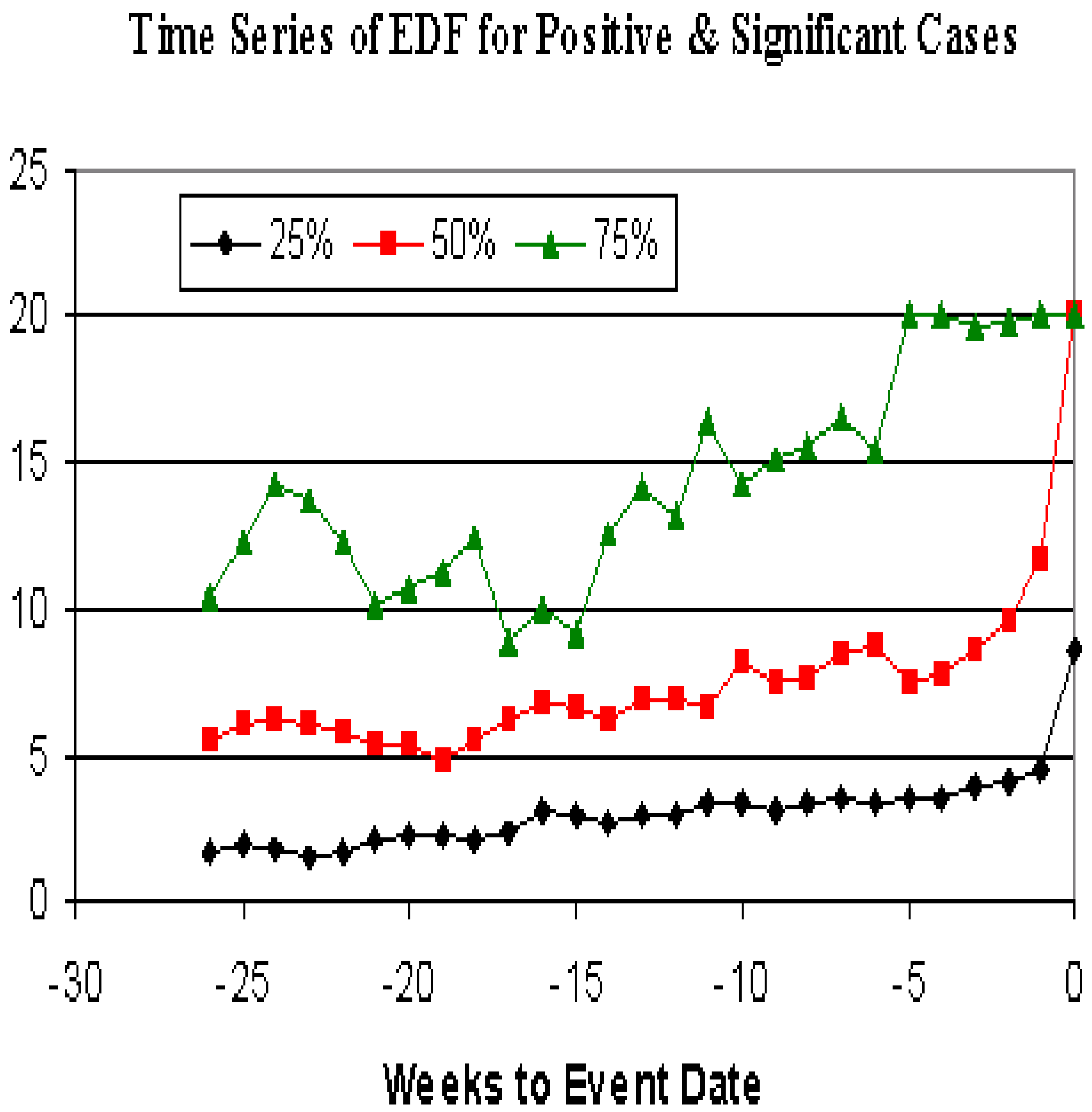

Figure 5: Time-series of MKMV EDF values for firms whose equity displayed a "surprise" on the arrival of distress. The time of distress is the first week when the bond of a firm falls by more than 20% over one week, or the formal announcement of distress, whichever comes first.

	Bankruptcy (Chapter 11)	Default	Distressed Exchange Offer Exchange Offer	Liquidation Bankruptcy (Chapter 7)	Subsidiary Default	Total
Observations	639	726	64	84	36	1549
Firms with Stocks	521	609	59	82	0	1271
Firms with Stocks & Bonds	21	26	5	0	0	52

Table 1: Distribution of distressed firms across different distress types, and across the availability of bond and stock data for them. The distribution is based on firms that went into distress between January, 1999 and June, 2004.

Time Horizon	Bankruptcy	Default	Distressed Exchange	Liquidation	Total
1 week Prior	151	98	18	6	273
2 weeks prior	237 (275)	178 (202)	33 (40)	14 (14)	462 (531)
4 weeks prior	318 (481)	280 (384)	45 (70)	23 (28)	666 (963)
26 weeks prior	465 (2003)	517 (1766)	74 (360)	50 (152)	1106 (4281)
1 week post	233	142	37	10	422
-1 day to +1 day	15	22	7	1	45

Table 2(a): Distribution of jumps (as defined by criterion (10(a))) that take place within a given time horizon of a distress event. Numbers represent the unique firms experiencing jumps. Each firm can experience multiple jumps. Numbers in parentheses represent total number of jumps. The distribution is based on firms that defaulted between January, 1999 and June, 2004.

Time Horizon	Bankruptcy	Default	Distressed Exchange	Liquidation	Total
1 week Prior	66	45	9	2	122
2 weeks prior	104 (115)	87 (91)	17 (18)	6 (6)	214 (230)
4 weeks prior	166 (202)	140 (168)	20 (27)	13 (14)	339 (411)
26 weeks prior	318 (500)	334 (514)	44 (71)	31 (41)	727 (1126)
1 week post	167	90	27	4	288
-1 day to +1 day	17	19	7	1	44

Table 2(b): Distribution of jumps (as defined by criterion (10(c))) that take place within a given time horizon of a distress event. Numbers represent the unique firms experiencing jumps. Each firm can experience multiple jumps. Numbers in parentheses represent total number of jumps. The distribution is based on firms that defaulted between January, 1999 and June, 2004.

Parameter	Estimate	Standard Error	95 % confidence Interval		Chi-square	Prob. > Chi-square
Intercept α	-0.8460	0.0296	-0.9040	-0.7880	816.84	< 0.0001
$Ln(EDF)\beta$	0.1379	0.0103	0.1178	0.1580	180.12	< 0.0001

Table 3: Probit analysis of defaults on MKMV default probabilities $I_{dit} = \alpha + \beta Ln\left(EDF_{it-1}\right)$. The data selected was for 44 days before default to 22 days after default. Number of non-default observations is 20459, while the number of default observations is 42628.

Percentiles	Number of Firms	Median π_e	Median t-statistic
< 10 %	98	-0.6643	-1.4791
10-20%	99	-0.0979	-1.1445
20-30%	97	-0.0428	-0.5926
30-40%	98	-0.0120	-0.1483
40-50%	99	0.0053	0.0570
50-60%	98	0.0248	0.2818
60-70%	98	0.0533	0.6446
70-80%	98	0.1057	1.0648
80-90%	98	0.2099	1.6451
90-100%	98	0.4385	2.7147

Table 4(a): OLS analysis of equity returns on market returns and firm-idiosyncratic returns conditional on firm-specific information as given by $R_{equity,it} = a_i + b_i R_{mt} + \pi_e \frac{\phi(\theta' X_{it-1})}{\Phi(\theta' X_{it-1})}(1 - I_{dit}) - \pi_e \frac{\phi(\theta' X_{it-1})}{1-\Phi(\theta' X_{it-1})} I_{dit} + \nu_{equity,it}$. The data selected was for 44 days before default to 22 days after default. Number of non-default observations is 20459, while the number of default observations is 42628.

Positive	570
Positive & Significant	110
Negative	411
Negative & Significant	52

Table 4(b): Description of π_e in the regression $R_{equity,it} = a_i + b_i R_{mt} + \pi_e \frac{\phi(\theta' X_{it-1})}{\Phi(\theta' X_{it-1})}(1 - I_{dit}) - \pi_e \frac{\phi(\theta' X_{it-1})}{1-\Phi(\theta' X_{it-1})} I_{dit} + \nu_{equity,it}$ in Table 4(a) in terms of size and significance.

Credit Event	Positive & Significant	Negative & Significant	Total
Bankruptcy (Chapter 11)	60	17	521
Default	37	33	609
Distressed Exchange Offer	3	1	59
Liquidation Bankruptcy (Chapter 7)	10	1	82
Total	110	52	1271

Table 5(a): Break-up of significant π_es in Table 4(b) by distress events.

Credit Event	π_e	t-statistic of π_e
Bankruptcy (Chapter 11)	0.162	4.04
Default	0.024	0.28
Distressed Exchange Offer	0.004	0.13
Liquidation Bankruptcy (Chapter 7)	0.224	0.68

Table 5(b): Description of π_e in the regression $R_{equity,it} = a_i + b_i R_{mt} + \pi_e \frac{\phi(\theta' X_{it-1})}{\Phi(\theta' X_{it-1})}(1 - I_{dit}) - \pi_e \frac{\phi(\theta' X_{it-1})}{1-\Phi(\theta' X_{it-1})} I_{dit} + \nu_{equity,it}$ where data is aggregated across distress events.

Variable		25^{th} Percentile	50^{th} Percentile	75^{th} Percentile
Size	Positive & Significant	2.99	4.90	6.23
	Negative & Significant	3.31	4.60	5.57
Leverage	Positive & Significant	0.672	0.833	1.142
	Negative & Significant	0.625	0.806	1.100
Asset Volatility	Positive & Significant	0.224	0.399	0.690
	Negative & Significant	0.289	0.488	0.771

Table 5(c): Size, leverage, and asset volatility distribution characteristics for significant π_es in Table 4(a) .

Parameter	Estimate	Standard Error	95 % confidence Interval		Chi-square	Prob. > Chi-square
Intercept α	-0.2272	0.0789	-2.3819	-2.0725	796.01	< 0.0001
$Ln(EDF)\beta$	0.0698	0.0274	0.0161	0.1236	6.49	0.0109

Table 6: Probit analysis of defaults on MKMV default probabilities $I_{dit} = \alpha + \beta Ln\left(EDF_{it-1}\right)$. The data selected was for 44 days before default till the day of default. Number of default observations is 922, while the number of non-default observations is 42628.

Percentiles	Number of Firms	Median π_e	Median t-statistic
< 10 %	98	-0.9418	-1.4099
10-20%	98	-0.0656	-1.1524
20-30%	98	-0.0280	-0.5709
30-40%	98	-0.0073	-0.1325
40-50%	98	-0.0042	0.0631
50-60%	98	0.0179	0.3052
60-70%	98	0.0390	0.6869
70-80%	98	0.0750	1.0599
80-90%	98	0.1464	1.6443
90-100%	98	0.2972	2.7476

Table 7(a): OLS analysis of equity returns on market returns and firm-idiosyncratic returns conditional on firm-specific information as given by $R_{equity,it} = a_i + b_i R_{mt} + \pi_e \frac{\phi\left(\theta' X_{it-1}\right)}{\Phi\left(\theta' X_{it-1}\right)}\left(1 - I_{dit}\right) - \pi_e \frac{\phi\left(\theta' X_{it-1}\right)}{1-\Phi\left(\theta' X_{it-1}\right)} I_{dit} + \nu_{equity,it}$. The data selected was for 44 days before default till the day of default. Number of default observations is 922, while the number of non-default observations is 42628.

Positive	578
Positive & Significant	111
Negative	402
Negative & Significant	49

Table 7(b): Description of π_e in the regression $R_{equity,it} = a_i + b_i R_{mt} + \pi_e \frac{\phi\left(\theta' X_{it-1}\right)}{\Phi\left(\theta' X_{it-1}\right)}\left(1 - I_{dit}\right) - \pi_e \frac{\phi\left(\theta' X_{it-1}\right)}{1-\Phi\left(\theta' X_{it-1}\right)} I_{dit} + \nu_{equity,it}$ in terms of size and significance.

Percentiles	Number of Firms	Median π_e	Median t-statistic
< 10 %	118	-0.4846	-1.6007
10-20%	118	-0.1096	-0.7184
20-30%	118	-0.0440	-0.3317
30-40%	118	-0.0034	-0.0308
40-50%	118	0.0318	0.2266
50-60%	118	0.0860	0.5621
60-70%	118	0.1621	0.9040
70-80%	118	0.2464	1.3251
80-90%	118	0.3736	2.0187
90-100%	118	0.5352	1.4105

Table 8(a): OLS analysis of equity returns on market returns and firm-idiosyncratic returns conditional on firm-specific information as given by $R_{equity,it} = a_i + b_i R_{mt} + \pi_e \frac{\phi(\theta' X_{it-1})}{\Phi(\theta' X_{it-1})} (1 - I_{dit}) - \pi_e \frac{\phi(\theta' X_{it-1})}{1-\Phi(\theta' X_{it-1})} I_{dit} + \nu_{equity,it}$. The data selected was for 44 days before default to 22 days after default. Number of default observations is 20459, while the number of non-default observations is 42628.

Positive	755
Positive & Significant	142
Negative	425
Negative & Significant	53

Table 8(b): Description of π_e in the regression $R_{equity,it} = a_i + b_i R_{mt} + \pi_e \frac{\phi(\theta' X_{it-1})}{\Phi(\theta' X_{it-1})} (1 - I_{dit}) - \pi_e \frac{\phi(\theta' X_{it-1})}{1-\Phi(\theta' X_{it-1})} I_{dit} + \nu_{equity,it}$ in terms of size and significance.

π_b	$Y_{it} = a_i + b_i R_{mt}$	$Y_{it} = a_i + b_i R_{mt} + \beta_{1b} R_{equity,it-1} + \beta_{2b} R_{equity,it-2}$
Positive	387	385
Positive & Significant	150	132
Negative	444	439
Negative & Significant	68	59

Table 9(a): Description of π_b in the regression $R_{bond,it} = Y_{it} + \pi_b \frac{\phi(\theta' X_{it-1})}{\Phi(\theta' X_{it-1})}(1 - I_{dit}) - \pi_b \frac{\phi(\theta' X_{it-1})}{1-\Phi(\theta' X_{it-1})} I_{dit} + \nu_{bond,it}$ in terms of size and significance.

π_b	$Y_{it} = a_i + b_i R_{mt}$	$Y_{it} = a_i + b_i R_{mt} + \beta_{1b} R_{equity,it-1} + \beta_{2b} R_{equity,it-2}$
Positive	41	40
Positive & Significant	18	17
Negative	30	31
Negative & Significant	8	7

Table 9(b): Description of π_b across unique number of firms in the regression $R_{bond,it} = Y_{it} + \pi_b \frac{\phi(\theta' X_{it-1})}{\Phi(\theta' X_{it-1})}(1 - I_{dit}) - \pi_b \frac{\phi(\theta' X_{it-1})}{1-\Phi(\theta' X_{it-1})} I_{dit} + \nu_{bond,it}$ in terms of size and significance.

	Regression 1			Regression 2		
	α_e	β_{1e}	β_{2e}	α_b	β_{1b}	β_{2b}
Parameter	-0.016	-0.010	0.025	-0.010	0.015	0.007
t-statistic	-6.19	-0.40	-0.99	-16.57	10.58	5.23

Table 10: Coefficients of regressions- Regression 1: $R_{equity,it} = \alpha_e + \beta_{1e} R_{bond,it-1} + \beta_{2e} R_{bond,it-2} + \epsilon_{eit}$, and Regression 2: $R_{bond,it} = \alpha_b + \beta_{1b} R_{equity,it-1} + \beta_{2b} R_{equity,it-2} + \epsilon_{bit}$.

π_b	Formally Distressed Firms Sample	Entire Sample
Positive	43	96
Positive & Significant	29	51
Negative	7	52
Negative & Significant	2	10

Table 11(a): Description of π_e in the regression $R_{equity,it} = a_i + b_i R_{mt} + \pi_e \frac{\phi(\theta' X_{it-1})}{\Phi(\theta' X_{it-1})}(1 - I_{dit}) - \pi_e \frac{\phi(\theta' X_{it-1})}{1-\Phi(\theta' X_{it-1})} I_{dit} + \nu_{equity,it}$ in terms of size and significance and across the types of distress. The definition of distress was based on the formal announcement of the distress event or the decline of bond price by more than 20% over a week, whichever came first.

Parameter	Estimate	Standard Error	95 % confidence Interval		Chi-square	Prob. > Chi-square
Intercept α	0.1418	0.0412	0.0611	0.2225	11.85	< 0.0006
Book Asset Value	-0.0375	0.0059	-0.0491	-0.0259	40.15	< 0.0001
Equity Volatility	-0.0054	0.0003	-0.0060	-0.0048	315.89	< 0.0001
$\frac{\text{Market Cap}}{\text{Market Cap + Total Liablities}}$	-0.8462	0.0713	-0.9861	-0.7064	140.71	< 0.0001
$\frac{\text{EBITDA}}{\text{Common Equity}}$	0.0000	0.0001	-0.0002	0.0003	0.02	0.8956

Table 12(a): Probit analysis of defaults on MKMV default probabilities $I_{dit} = \alpha + \beta X_{it-1}$ where X_{it-1} is a vector of accounting and market variables. The data selected was for 12 months before default till 6 months after default. Number of default observations is 1110, while the number of non-default observations is 5459.

Positive	753
Positive & Significant	112
Negative	473
Negative & Significant	64

Table 12(b): Description of π_e in the regression $R_{equity,it} = a_{e,i} + b_{e,i}R_{mt} + \pi_e \frac{\phi(\theta' X_{it-1})}{\Phi(\theta' X_{it-1})}(1 - I_{dit}) - \pi_e \frac{\phi(\theta' X_{it-1})}{1-\Phi(\theta' X_{it-1})} I_{dit} + \nu_{equity,it}$ in terms of size and significance.