Distress Risk Anomaly During Market Crises

Bachelor’s Thesis
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Abstract
I study the relationship between distress risk and returns during market crises. I find that over a period from 1973 to 2020 this relationship is negative, which is why it is called the distress risk anomaly. However, during market crises, this relationship reverses completely and becomes positive. This finding indicates that the anomaly is driven by systematic default risk as it is elevated during times of crisis. Only the systematic portion of total default risk is compensated with higher returns. Thus the negative relationship between distress risk and returns over a long period is likely due to the inability to capture systematic default risk.

Keywords Distress risk anomaly, Systematic default risk, High-yield spreads
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1 Introduction

Distress risk anomaly is an irregularity in the markets in which companies with higher distress risk produce lower returns over longer periods. (Dichev, 1998; Campbell et al., 2008; Andreou et al., 2020) Distress risk, also known as default risk, is measured as the probability for a company to default. In this paper, I attempt to show how the distress risk anomaly behaves during times of crisis observing a period from 1973 to 2020. By studying the anomaly during crisis periods my contributions are twofold. First, I provide an understanding of the anomaly’s behaviour during crises, which has not been studied before. Second, by understanding the anomaly during crises, I can use this knowledge to infer a better explanation for the anomaly’s lower returns over longer periods.

When a crisis hits the markets and panic begins to rise, the distress risk anomaly makes a complete reversal and yields higher returns the more distress risk there is. I believe this outcome is due to elevated systematic default risk and the ability to better measure it during crisis periods, which is then compensated by higher returns. This finding supports the notion that the anomaly’s negative returns during longer periods are because of the inability to capture systematic risk.

The distress risk anomaly, supported by a large body of empirical research, seems to conflict with the traditional view of how taking more distress risk should be rewarded with higher returns (Fama and French, 1995, 1996; Chan and Chen, 1991). On the other hand, it could be claimed that markets only reward systematic risk with higher rewards, not total risk.1 Perhaps the anomaly is partially caused by the inability to adequately measure and capture systematic default risk – a component of systematic risk – as is suggested by Dichev (1998). What then happens to the return structure of distress risk during crises when the distress risk rises everywhere in the markets? Studying times of market panic allows me to better understand the impact of systematic default risk on the anomaly.

2 Literature review

There is a significant amount of research focused on the distress risk anomaly. I will not attempt to explain all of it as that would require a book or two. Instead, I shall focus only on the literature most relevant to this study. Most studies have concluded higher distress risk to result in lower returns, and vice versa (see Dichev, 1998; Campbell et al., 2008; Andreou et al., 2020; Gao et al., 2018; Griffin and Lemmon, 2002, Eisdofer et al., 2013). In this study, I find a negative relationship between distress risk and returns as well. However, some studies have found the opposite effect in which higher distress risk has resulted in higher subsequent

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1 The widely used capital asset pricing model (CAPM) developed by Sharpe (1964), Treynor (1962), Lintner (1965a, 1965b) and Mossin (1966) assumes that only the non-diversifiable systematic risk is compensated with higher returns.
returns (see Anginer and Yildizhan, 2018; Vassalou and Xing, 2004; Aretz et al., 2018; Chava and Purnanandam, 2010).

Explanations for the anomaly vary to a large extent. Many studies claim that the anomaly is caused by mispricing or misvaluation (see Andreou et al., 2020; Campbell et al., 2008; Dichev, 1998; Eisdofer et al., 2013; Gao et al., 2018). However, that is hardly a sufficient explanation for the anomaly. Andreou et al. (2020) argue that earnings management could be one cause for the mispricing. Campbell et al. (2008) believe that firms with high distress risk have characteristics that appeal to certain investors such as increased opportunities to extract private benefits of control or positive skewness of returns. Eisdofer et al. (2018) attribute the anomaly to investors not fully considering the optionality of equity. Gao et al. (2018) suggest that the underreaction bias could be causing the anomaly. Fama and French (1996) argue that small minus big (SMB) and high minus low (HML) factors act as a proxy for default risk. However, Dichev (1998) contends that SMB and HML factors are unlikely to be a proxy for default risk, contrary to Fama and French (1996). Griffin and Lemmon (2002) claim that investors overreact to the future growth potential of distressed firms too quickly. Avramov (2010) argues that the distress risk anomaly is because companies with higher distress risk have lower systematic default risk and consequently lower returns. Related to Avramov’s (2010) findings, Aretz et al. (2018) and Anginer and Yildizhan (2018) also find systematic default risk to be the main driver of returns when observing the anomaly. It seems quite clear that the general view on the anomaly’s explanation is mixed and that most likely the true answer is a combination of various explanations. In this study, I contribute to the explanation that systematic default risk is the main driver of returns behind the anomaly.

Numerous methods have been developed to better measure the distress risk of companies and the idea behind most of them is to estimate a rough probability of default. However, there is no definitive and absolute way of measuring distress risk. The measures can be roughly divided into market-based and accounting-based measures of distress risk. Accounting-based measures use firms’ fundamental information. These include Altman’s (1968) Z-score, Ohlson’s (1980) O-score and Piotroski’s (2000) F-score. Market-based measures incorporate data that is derived from market information such as market equity or bond yields. These include Moody’s KMV model, Merton’s (1974) distance to default model, credit default swaps used by Friewald et al. (2014), and bond yield spreads used by Bharath and Shumway (2008). I use Merton’s distance to default model with a slight modification made by Bharath and Shumway (2008).
3 Theoretical background

3.1 Using high yield spreads to choose crisis periods

Before I can analyse the anomaly during times of crisis, I need to find an effective method to choose the crisis periods. Defining crisis periods is by no means a straightforward task. Instead of choosing the crisis periods arbitrarily, I shall use high yield (“HY”) spreads as an indicator for a crisis because they have significant explanatory power for the business cycle and thus effectively can indicate when the markets might be deemed to be in a crisis (see Gertler and Lown, 2000). In this study, high yield spreads are calculated as the yield on high yield bonds minus the yield on U.S. Treasury bonds. Gertler and Lown (2000) find that HY spreads outperform other prominent financial indicators such as the term spread, paper-bill spread and fed funds rate. Specifically, I shall choose crisis periods as months during which the spreads are elevated above a specific threshold following Rasmussen (2020).

The HY spreads are a good indicator of the business cycle because of their ability to measure the external financing premium. The external financing premium is the spread between the cost of external finance and the opportunity cost of internal finance. Companies that fall within the high yield group are likely to represent the wide group of firms that have imperfect access to credit. These companies are also not perceived as very safe. This imperfect access to credit and lack of being perceived as safe is reflected in the cost of external financing much better. As a result, the high yield bonds’ spread becomes an excellent proxy for the external financing premium. (Gertler and Lown, 2000) But what makes the external financing premium important?

The external financing premium can provide vital information on the current financial conditions within the economy and the markets. (Bernanke and Gertler, 1989) In particular, the premium gives insight into the net worth of the borrowers, who represent nearly all companies. This is because a borrower’s net worth is positively correlated with the agency costs of external financing, which means that when a borrower’s net worth decreases, the cost of external financing increases. The reason for this increase is that when the net worth goes down, lenders will naturally want higher compensation for financing because they have fewer assets to receive as collateral and because of the lack of information on the borrower. The higher agency cost can be thought of as higher compensation for higher risk. Lower net worth and higher external financing costs result in decreased investments within the company and thus overall in the economy as well because the companies are receiving less financing. Lower investments then amplify the downturns and can give information on when the economy is heading towards crisis periods. Therefore, a higher premium indicates “bad” and “good” times in the economy and the markets. (Bernanke and Gertler, 1989; Bernanke and Gertler, 1999)
Another simpler explanation for the HY spreads’ capability to indicate upturns or downturns is that higher spreads mean higher compensation as a reward for higher risk from lending to the companies rated in the high yield group. Higher risk is measured as how much higher returns above the risk-free rate investors are requiring from companies, hence the spreads and not the total yields. If the risk is overall higher everywhere in the markets, then we might assume that the investors are assuming there to be some type of a market-wide crisis period at hand, which is affecting most companies.

The corporate bond spreads, of which the HY spreads are part of, have been found to incorporate a significant risk premium for systematic default risk (see Elton et al. 1999; Huang and Huang, 2012; Berndt et al., 2004). The premia compensated for systematic default risk becomes higher when the spreads become higher. Therefore, the crisis periods I choose will naturally encompass periods when the systematic default risk is higher.

3.2 Systematic default risk explains the distress risk anomaly

Understanding systematic default risk requires a simple categorisation of total risk. Total risk is divided into systematic and idiosyncratic risk. Simply put, systematic risk impacts all firms while idiosyncratic risk is firm-specific. Because you can diversify idiosyncratic risk, markets do not reward excess returns for taking more idiosyncratic risk. Systematic risk on the other hand cannot be diversified away and thus is compensated with higher returns. Both systematic and idiosyncratic risk can be divided into further subcomponents, such as default risk that can be both systematic and idiosyncratic.² The main focus of this study is on the systematic default risk. Systematic default risk is therefore a subcomponent of total systematic risk. It is the risk of default that impacts the economy-wide default probabilities of all companies (see Anginer and Yildizhan, 2018; Kim, 2019). This also means that it must be compensated because you cannot diversify it away.

I believe that the behaviour of the distress risk anomaly can be explained by systematic default risk, following Avramov (2010), Aretz et al. (2018) and Anginer and Yildizhan (2018). I support this explanation with my findings on the anomaly during crisis periods. I argue that during periods of crisis, systematic default risk increases. This systematic default risk is then better captured during market panic as its relative portion of total default risk increases. Using the HY spreads to choose the crisis periods is further evidence that the systematic default risk is elevated during crises. The anomaly then reverses during crises because higher systematic default risk is compensated with higher returns.

Naturally, no crisis is alike and pinpointing the exact cause behind a crisis can often be difficult. However, I believe that one source of increased systematic default risk can be found in the real economy itself. To

² In this paper the term default risk is used interchangeably with distress risk.
some extent, this comes through the interrelatedness of all the economic actors. No company can function in a vacuum without being related to other companies. This relationship makes companies dependent on each other both in good and bad. In times of crisis, this means that a default of one company can cause a default in another company, which in turn increases the contagion and correlation of defaults everywhere. Again, this type of default risk is inherent to all companies making it systematic.

Another source of increased systematic default risk is investor behaviour during crises, which causes major fluctuations in the financial markets. These fluctuations come in the form of liquidity issues and market crashes. These issues in the financial markets can have a massive negative impact on the real economy for example through less financing or increased fear causing less spending. An example of this causal relationship is the global financial crisis in 2008 (see Kenourgios and Dimitriou, 2015). Lastly, the negative impact on the real economy increases the default probabilities of all firms and further amplifies the contagion and correlation of defaults as described above.

3.3 Merton distance to default as a measure of distress risk

Distress risk can be measured in a plethora of various methods. Out of the various methods to measure distress risk, I use the Bharath and Shumway (2008) modified form of Merton’s (1974) distance to default (“DD”) model. I chose the model because it is forward-looking, useful and accurate for predicting defaults, and sufficiently easy to calculate for this study (see Bharath and Shumway, 2008; Chen and So, 2014; Andreou et al., 2020). The DD model utilizes the Black and Scholes (1973) and Merton (1974) options pricing model to calculate a probability of default for a company. This measure is then used to represent the amount of distress risk within each company.

The forward-looking nature of the model makes it better than alternative accounting-based models. Instead of using only accounting data, such as Altman’s (1968) Z-score, the DD model combines both accounting data and market data. Value and volatility of equity are utilized as inputs in calculating an implied probability of default, which makes the model forward-looking as the market data includes investors’ expectations of the observed companies.

The Bharath and Shumway (2008) modified version is relatively easy to calculate compared to the original Merton DD model. For example, instead of having to use an iterative procedure, the model calculates the probability of default by solving just one equation and calculating the cumulative standard normal distribution function. The modified model still retains the structure of the Merton model, encapsulates roughly the same information, and uses the same inputs. It is even a slightly better predictor of defaults than the Merton model according to Bharath and Shumway (2008).
4 Data and methodology

4.1 Data

My sample data consists of stocks listed on NYSE, Amex, and NASDAQ between January 1973 and December 2020. The data is acquired by combining CRSP Monthly and Compustat Quarterly data. I exclude financial firms identified by SIC codes 6000 to 6999. I pair quarterly fundamental data with market data three months after the end of the fiscal quarter to reduce the impact of the look-ahead bias and ensure that fundamental data is known to investors and properly reflected in market prices. This data set allows me to obtain an initial sample of 1,440,158 firm-month observations for the analysis.

4.2 Distress risk measure

The Bharath and Shumway (2008) modified formula of the Merton DD for measuring distress risk is:

$$DD_{BS} = \frac{\ln \left( \frac{V}{D} \right) + (R_{t-1} - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}}.$$  

In which $V$ is the total assets of the firm and calculated as market value of equity (E) + face value of debt (D). The Market value of equity (E) is calculated as total shares outstanding (CRSP “shrout”) multiplied by share price (CRSP “prc”). Following Vassalou and Xing (2004) and Crosbie and Bohn (2003), face value of debt (D) is calculated as debt in current liabilities (Compustat “dlcq”) plus half long-term debt (Compustat “dlttq”). $R_{t-1}$ is calculated as annual equity returns (CRSP “ret”) at month $t-1$. T is the forecast horizon, which is set to 1 year.

The firm volatility ($\sigma_V$) is calculated as a weighted arithmetic mean of the equity volatility ($\sigma_E$) and the debt volatility ($\sigma_D$) of the firm:

$$\sigma_V = \left( \frac{E}{E + D} \right) \sigma_E + \left( \frac{D}{E + D} \right) \sigma_D.$$  

Equity volatility is the annualized standard deviation of monthly equity returns from the past 36 months. Following Andreou et al. (2020), equity returns are calculated as the continuously compounded rate of return on equity, which is adjusted for cash dividends (CD) (Compustat “dvpsx”):

$$R_E = \ln \left( \frac{E_t + CD_t}{E_{t-1}} \right).$$

Debt volatility is estimated with an approximation formula using equity volatility as an input: $\sigma_D = 0.05 + 0.25\sigma_E$. 
The probability of default is then calculated by taking the cumulative standard normal distribution function of $-DD_{BS}$:\(^3\)

$$\text{Probability of default} = \Phi(-DD_{BS}).$$

To test the robustness of the results, I use the Charitou et al. (2013) modified version of the Bharath and Shumway (2008) form of the Merton DD model as an alternative measure of distress risk. The Charitou et al. (2013) version is otherwise calculated in the same manner as Bharath and Shumway (2008) except that they do not use the approximation formula for calculating debt volatility. Instead, they calculate firm volatility directly from the changes in total assets ($V$). Following Andreou et al. (2020) the firm volatility is calculated from total asset returns from the past 36 months. Asset returns are calculated as the continuously compounded rate of return on assets, adjusted for cash dividends ($CD$) (Compustat “dvpsx”) and interest expenses ($IE$) (Compustat “xintq”):

$$R_V = \ln\left(\frac{V_t + CD_t + IE_t}{V_{t-1}}\right).$$

Everything else is calculated using the Bharath and Shumway (2008) form. This change in the calculation of volatility gives $DD_C$ as the alternative distress risk measure.

### 4.3 Crisis periods

Following Rasmussen (2020) I calculate crisis periods by picking months when the bond spreads are higher than the mean of the spreads plus one standard deviation for the whole period. As a proxy for the high yield spreads, I use Moody’s Baa corporate bond spread over the 10-year constant maturity treasury obtained from the Federal Reserve Bank of St. Louis. Optimally I would have used the BofA High Yield Master II Index to best reflect the high yield spreads, but it only goes back to 1996 whereas the Baa corporate bond spreads go back to 1953. Further, both spreads have a correlation of 0.92 for the overlapping period between 1996 and 2020, and the Baa corporate bond spreads are the closest alternative to high yield spreads in terms of the level of risk. I acknowledge that using the Baa spreads decreases the accuracy to some extent. However, this sacrifice allows me to study a much longer time frame, and I only require the months when the spreads elevate beyond a threshold and start showing panic within the markets. Thus, for the purposes of this study, this level of inaccuracy is acceptable. The small sacrifice in the accuracy of the spreads is worth the much longer data period, which is from 1973 to 2020.

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\(^3\) Even though this assumes normality, it does not impact the results of my study in any way. The results are exactly same whether I use the raw distress risk measure $DD_{BS}$ or whether it is converted into a probability of default.
Using the Baa bond spreads, I calculate 1.92% as the arithmetic mean and 0.82% as the standard deviation. Therefore, the threshold is 1.92% + 0.82% = 2.74%. This threshold gives me 132 crisis months out of a total of 576 months between 1973 and 2020 surrounding the crises in years 1974, 1980, 1986, 2000, 2008, 2012, 2016 and 2020. Crisis periods are illustrated in Figure 1 with brief descriptions of the crisis periods.

**Figure 1**

**Baa Corporate Bond Spreads and Crisis periods**

Figure 1 displays the dates during which Baa Corporate Bond Spreads are above the threshold of 2.74% represented by the red horizontal line. Crisis periods are in orange colour and their causes are briefly explained. The time horizon is from January 1973 to December 2020. Data is acquired from the Federal Reserve Bank of St. Louis.

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**4.4 Portfolio analysis**

Based on the probability of default calculated from the distress risk measure, the stocks are sorted into ten portfolios and rebalanced each month. Then I calculate value-weighted returns of each portfolio 1 to 10 during each month. Lastly, I compare both mean raw and risk-adjusted monthly returns both for the crisis periods as well as the full period. Raw monthly returns are calculated using the arithmetic mean. Risk-adjusted monthly returns are calculated using the Fama and French (2015) 5-factor model with the following regression:

\[ R_{it} - R_{ft} = \alpha_i + \beta_i(R_{Mt} - R_{ft}) + s_iSMB_t + h_iHML_t + r_iRMW_t + c_iCMA_t + \epsilon_{it} . \]
Here the $R_{it}$ is the value-weighted portfolio return, $R_{ft}$ is the risk-free return, $\alpha_i$ is the risk-adjusted return not explained by the factors, $R_{Mt}$ is the value-weighted market portfolio return, $R_{Mt} - R_{ft}$ is the market risk factor, $SMB_t$ is the difference between small and big capitalization firms, $HML_t$ is the difference between high and low B/M firms, $RMW_t$ is the difference between robust and weak profitability firms and $CMA_t$ is the difference between firms with conservative and aggressive investments. Data for the 5-factor model was acquired from the Kenneth R. French data library.

In order decrease the impact of survivorship bias I control for delisted returns using the method described in Bali et al. (2016), which is based on Shumway’s (1997) approach. This correction is possible because the CRSP database includes data on delisted companies enabling me to better control for them. Furthermore, to make sure that the results are not heavily influenced by outliers, I winsorize the observations at the 1st and 99th percentiles.

5 Empirical results

5.1 Main findings

Table 1 displays raw and risk-adjusted value-weighted returns for each portfolio chosen by sorting all firms into 10 deciles based on the amount of distress risk. These returns are calculated first for the full period from 1973 to 2020 and then only to the crisis periods when the Baa corporate bond spreads are above the 2.74% threshold.

The first main finding is that during the crisis period, distress risk is positively correlated with both raw and risk-adjusted returns. Higher distress risk yields higher returns. The highest distress risk portfolio (10) yielded 1.77 percentage points raw and 1.13 percentage point risk-adjusted monthly returns more than the lowest distress risk portfolio (1).

The second main finding is that over the full period, distress risk is negatively correlated with risk-adjusted returns. However, the negative correlation was not highly present for the raw returns. The highest distress risk portfolio (10) had $-1.02$ percentage points risk-adjusted monthly returns more than the lowest distress risk portfolio (1) but only $-0.2$ percentage points more for the raw returns. Consistent with past research, this finding leads me to believe that the distress risk anomaly still exists over a long period of time but that the effect of the anomaly might have dissipated to some extent.

Comparing both the crisis and full period results, I find that during the full period the premium for distress risk is negative but that during crisis periods this effect is completely reversed. This finding supports my explanation of how during the crisis periods the elevated systematic default risk is better captured, which
results in higher returns because only the systematic default risk component is compensated. The findings could also suggest that during market panic, the companies with the most distress risk are being oversold.

Table 1
Monthly portfolio returns: crisis and full period

The table shows risk-adjusted and raw value-weighted returns of portfolios sorted based on distress risk. Distress risk is measured using $DD_{BS}$. Raw return is the monthly arithmetic mean return. Risk-adjusted return is calculated using Fama and French (2015) 5-factor model. Portfolios are rebalanced monthly with portfolio 10 having the highest distress risk and 1 having the lowest distress risk. The full period is all months between January 1973 and December 2020. Crisis periods are chosen as months when Baa corporate bond spreads are above 2.74%. t-statistics are in parentheses and coloured in orange. *, ** and *** denote significance at 10%, 5% and 1% respectively.

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Crisis period</th>
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<th>Full period</th>
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<td>Risk-Adjusted Return</td>
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<td>10 (highest)</td>
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<td>(1.97)*</td>
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<td>(3.03)***</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Highest–Lowest</td>
<td>1.13%</td>
<td>1.77%</td>
<td>-1.02%</td>
<td>-0.2%</td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

5.2 Limitations and criticisms

Limitations of the analysis and results include the lack of significance, especially in the highest distress risk portfolios. For instance, the risk-adjusted returns of the two highest distress risk portfolios (9 and 10) were
not significant at 5% both during the crisis and full period. This lack of significance suggests two things. The first is that the distress risk anomaly over the full period might not be that prominent. The second is that the reversal of the distress risk anomaly during market panic is not necessarily that amplified.

Further criticism could focus on the length of my holding period as well as the transaction costs. I use a holding period of 1 month, which might be argued to be too short to properly represent the impact of a crisis on a firm’s stock. The returns presented in Table 1 are also before transaction costs, which might become quite hefty as the portfolios are rebalanced each month. I believe that both of these criticisms would be more relevant only if the focus were to create an optimal investing strategy rather than understanding a phenomenon in the markets. My main attempt is the latter and thus the dynamic change in monthly returns gives me the best information regarding the shifts in systematic default risk. Consequently, this method allows me to best understand how the anomaly behaves.

The high risk-adjusted returns during the crisis periods might pose a problem for the strength of my explanation regarding the anomaly. In this paper, I argue that the anomaly is driven by the systematic default risk, but in Table 1 we can see that the returns during crisis periods persist even after adjusting for Fama and French (2015) 5-factor model. This observation raises the question that if the anomaly is driven by systematic default risk, why do the returns not dissipate when adjusting for Fama and French (2015) 5-factor model? After all, market risk is one of the factors in the Fama-French model. This finding might indicate that there is another unknown element besides the systematic default risk driving the returns. My explanation for this problem is that the Fama and French (2015) 5-factor model simply cannot capture the systematic default risk sufficiently enough.

5.3 Robustness
Using the Charitou et al. (2013) alternative distress risk measure $DD_C$, I find results that confirm my main findings from using the Bharath and Shumway (2008) distress risk measure $DD_{BS}$. There are however two small differences. The first difference to the main findings is that the negative relationship between distress risk and returns over the full period is found both for risk-adjusted returns and raw returns. The highest–lowest (10–1) portfolio risk-adjusted return was $-1.47\%$ (compared to $-1.02\%$ using $DD_{BS}$) and the raw return was $-0.65\%$ (compared to $-0.2\%$ using $DD_{BS}$). The second difference is that the reversal of the distress risk anomaly during crisis periods is not as strong both for risk-adjusted and raw returns. During the crisis periods, the highest–lowest (10–1) portfolio risk-adjusted return was $0.55\%$ (compared to $1.13\%$ using $DD_{BS}$) and the raw return was $1.19\%$ (compared to $1.77\%$ using $DD_{BS}$). The results are more detailed in the Appendix. Overall, the results from the alternative distress risk measure $DD_C$ confirm my main findings and the robustness of my results.
6 Conclusions

The main contribution of this paper to the existing literature is that I analyse the distress risk anomaly during periods of crisis and find that the distress risk anomaly reverses completely and rewards higher distress risk with higher returns. The distress risk is measured using the Bharath and Shumway (2008) modified version of the Merton (1974) distance to default model. The crisis periods are chosen as months when the high yield spreads are above a specific threshold following Rasmussen (2020).

The second key contribution is that the anomalously low returns caused by the distress risk anomaly still exist over a longer horizon ranging from 1973 to 2020, which is consistent with past literature on the negative relationship between returns and distress risk. However, I also find that the effect of the distress risk puzzle is not that prominent over the full horizon.

My explanation for the findings is that during a market crisis the systematic default risk increases and its proportion out of total risk also increases. Thus, the distress risk measure can capture more of the systematic default risk, which results in higher returns. This explanation also suggests that the negative returns during normal times could be due to lack of systematic default risk being captured by the distress risk measure. However, the systematic default risk itself is most likely not enough to explain the low returns caused by the anomaly over the full period. The lower returns could be caused by a myriad of other reasons such as earnings management according to Andreou et al. (2020) or specific characteristics of distressed firms that appeal to investors according to Campbell et al. (2008). Nonetheless, my findings still support Avramov’s (2010), Aretz et al. (2018), and Anginer’s and Yildizhan’s (2018) explanations that the distress risk anomaly is mainly driven by systematic default risk.

Panic caused by the recently discovered Covid-19 Omicron variant or perhaps something completely new and unexpected might throw the markets into a frenzy and even cause a major stock market crash. This panic could serve as a great opportunity to utilize the reversal of the distress risk anomaly that happens during a crisis. Investing while everyone else is panicking might be highly profitable, that is if you are not panicking as well.
Appendix – Alternative distress risk measure

Table A1 shows the portfolio returns obtained using the alternative distress risk measure $DD_C$ by Charitou et al. (2013) as described in section 4.2. During the crisis periods, the relationship between returns and distress risk is positive. This observation seems to apply both for the risk-adjusted and the raw returns. The risk-adjusted highest minus lowest portfolio return is 0.55% and the raw highest minus lowest portfolio return is 1.19%. It is worthwhile to note that the risk-adjusted returns of portfolios 8, 9 and 10 during the crisis periods are not significant at 10% significance level. This could indicate the results being purely due to chance or that the impact of the reversal is not as massive as I might conclude.

Regarding the full period returns, a notable finding is that the negative relationship between returns and distress risk is found both for raw and risk-adjusted returns. Highest minus lowest is $-1.47\%$ for the risk-adjusted return and $-0.65\%$ for the raw returns. These do not suffer from a lack of statistical significance as the crisis period returns might.

In general, I conclude that the findings using the alternative measure support my main findings described in section 5.1 and overall conclusions regarding the distress risk anomaly. However, one criticism of this robustness check is that it is fairly similar to the main measure used to evaluate distress risk. Therefore, it might not come as the biggest surprise that the results from the alternative measure are not that different from the main results.

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Crisis period</th>
<th></th>
<th>Full period</th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Risk-Adjusted Return</td>
<td>Raw Return</td>
<td>Risk-Adjusted Return</td>
<td>Raw Return</td>
</tr>
<tr>
<td>1 (lowest)</td>
<td>0.64%</td>
<td>1.34%</td>
<td>0.73%</td>
<td>1.62%</td>
</tr>
<tr>
<td></td>
<td>(4.11)***</td>
<td>(4.03)***</td>
<td>(7.55)***</td>
<td>(9.36)***</td>
</tr>
<tr>
<td>2</td>
<td>0.66%</td>
<td>1.52%</td>
<td>0.48%</td>
<td>1.58%</td>
</tr>
<tr>
<td></td>
<td>(4.18)***</td>
<td>(3.83)***</td>
<td>(5.61)***</td>
<td>(8.16)***</td>
</tr>
<tr>
<td>3</td>
<td>0.58%</td>
<td>1.43%</td>
<td>0.42%</td>
<td>1.54%</td>
</tr>
<tr>
<td></td>
<td>(3.56)***</td>
<td>(2.92)***</td>
<td>(4.35)***</td>
<td>(7.61)***</td>
</tr>
</tbody>
</table>

Table A.1

Monthly portfolio returns: crisis and full period

The table shows risk-adjusted and raw value-weighted returns of portfolios sorted based on distress risk. Distress risk is measured using $DD_C$. Raw return is the monthly arithmetic mean return. Risk-adjusted return is calculated using Fama and French (2015) 5-factor model. Portfolios are rebalanced monthly with portfolio 10 having the highest distress risk and 1 having the lowest distress risk. The full period is all months between January 1973 and December 2020. Crisis periods are chosen as months when Baa corporate bond spreads are above 2.74%. t-statistics are in parentheses and coloured in orange. *, ** and *** denote significance at 10%, 5% and 1% respectively.
<table>
<thead>
<tr>
<th></th>
<th>0.7%</th>
<th>1.64%</th>
<th>0.36%</th>
<th>1.54%</th>
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<tr>
<td>4</td>
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<td>(2.78)***</td>
<td>(3.58)***</td>
<td>(6.79)***</td>
</tr>
<tr>
<td>5</td>
<td>0.66%</td>
<td>1.65%</td>
<td>0.35%</td>
<td>1.54%</td>
</tr>
<tr>
<td></td>
<td>(2.37)**</td>
<td>(2.69)***</td>
<td>(3.00)***</td>
<td>(6.62)***</td>
</tr>
<tr>
<td>6</td>
<td>0.52%</td>
<td>1.44%</td>
<td>0.15%</td>
<td>1.39%</td>
</tr>
<tr>
<td></td>
<td>(1.91)*</td>
<td>(2.12)**</td>
<td>(1.28)</td>
<td>(5.53)***</td>
</tr>
<tr>
<td>7</td>
<td>0.87%</td>
<td>1.69%</td>
<td>0.3%</td>
<td>1.56%</td>
</tr>
<tr>
<td></td>
<td>(2.45)**</td>
<td>(2.08)**</td>
<td>(2.07)**</td>
<td>(5.55)***</td>
</tr>
<tr>
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<td>–0.11%</td>
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</tr>
<tr>
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<td>(0.43)</td>
<td>(1.7)*</td>
<td>(–0.67)</td>
<td>(4.47)***</td>
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<tr>
<td>9</td>
<td>0.59%</td>
<td>1.59%</td>
<td>–0.13%</td>
<td>1.39%</td>
</tr>
<tr>
<td></td>
<td>(1.04)</td>
<td>(1.42)</td>
<td>(–0.63)</td>
<td>(3.74)***</td>
</tr>
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<td>10 (highest)</td>
<td>1.19%</td>
<td>2.53%</td>
<td>–0.74%</td>
<td>0.97%</td>
</tr>
<tr>
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<td>(1.3)</td>
<td>(1.78)*</td>
<td>(–2.52)**</td>
<td>(2.13)**</td>
</tr>
<tr>
<td>Highest–Lowest</td>
<td>0.55%</td>
<td>1.19%</td>
<td>–1.47%</td>
<td>–0.65%</td>
</tr>
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</table>
References


