

Article

Financial Distress Premium or Discount? Some New Evidence

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Abstract: This study investigates the contradiction in the finding of a positive distress risk premium in Vassalou and Xing's study and the finding of a negative distress risk premium, i.e., a distress risk discount, in several other studies. Using the default likelihood measure calculated following Vassalou and Xing's procedure for 1965–2023, we show that excluding outliers and including the time period beyond the end of Vassalou and Xing's sample period in 1999 makes a difference in the results. Overall, using portfolio sorting and Fama-MacBeth regressions, this study supports the existence of a distress risk discount. This study also documents that the financial distress risk is negatively reflected in security prices even after accounting for size and book-to-market risk factors. Furthermore, it demonstrates that the negative distress risk premium is strong and persistent across economic expansions, recessions, and the COVID-19 pandemic.

Keywords: default likelihood; financial distress risk; economic regimes; asset pricing



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1. Introduction

Investors require excess returns above the risk-free rate as compensation for the higher uncertainty associated with risky assets. A major risk factor for a firm, financial distress risk, arises from its ability to meet its financial obligations to its bondholders, consequently requiring adequate compensation for investors. Investors should demand higher returns to hold equities as the likelihood of a firm's failure to meet its debt obligations increases. Riskier projects should offer higher returns as compensation for the increased risk associated with financial distress, bankruptcy, and default. We define the expected higher required rate of returns due to the financial distress risk as the financial distress risk premium.

Several studies in the prior literature examine distress risk in the context of empirical asset pricing, producing contradictory findings. Some studies, such as Vassalou and Xing's (2004) study, find that returns should be higher for high-distress-risk firms than low-distress-risk firms yielding a distress risk premium. On the other hand, several other studies, such as those by Dichev (1998), Campbell et al. (2008), Garlappi and Yan (2011), George and Hwang (2010), Griffin and Lemmon (2002), and Opler and Titman (1994), find distress risk to yield a discount instead of a premium.

Some studies that find a distress risk premium use the book-to-market equity (BM) ratio as a proxy for financial distress. Fama and French (1993) propose that a firm's sensitivity to a systematic distress factor is captured by its BM ratio. Consistent with this view, Chen et al. (2008) and Fama and French (1996) find that high (low) BM ratios forecast poor (strong) future earnings. Fama and French (1996) also document that firms in financial distress have higher required rates of return because of their higher distress risk.

Some studies on financial distress risk focus on the ability of the default spread to explain cross-sectional variation in stock returns. However, Elton et al. (2001) show that most of the information in the default spread is unrelated to financial distress risk. Vassalou and Xing (2004) use Merton's (1974) option pricing model to compute default measures for individual firms and assess the effect of default risk on equity returns. They find the

presence of distress risk premium. [Da and Gao \(2010\)](#) document that the positive distress risk premium shown by [Vassalou and Xing \(2004\)](#) is driven by short-term reversal.

In contrast to [Vassalou and Xing \(2004\)](#), the results from several other studies examining the distress risk premium in equity pricing contradict rational asset-pricing theory. Specifically, these studies document that, relative to low-distress-risk firms, high-distress firms earn lower subsequent stock returns. [Dichev \(1998\)](#) uses [Ohlson's \(1980\)](#) O-score and [Altman's \(1968\)](#) Z-score to proxy for distress risk and finds a negative relationship between stock returns and default probability. [Opler and Titman \(1994\)](#), [Griffin and Lemmon \(2002\)](#), and [George and Hwang \(2010\)](#) use the O-score as well to capture distress risk. These studies also document a negative relationship. [Liu et al. \(2023\)](#) finds a similar relationship in China. [Von Kalckreuth \(2005\)](#) argues theoretically that the reason for negative excess returns of highly distressed firms is that some owners can extract benefits from those firms. [Ozdagli \(2013\)](#) also proposes a theoretical model to explain the negative excess returns of highly distressed firms. The basis of this model is differentiating real probabilities of default from risk-neutral probabilities of default.

[Campbell et al. \(2008\)](#) uses the hazard model to predict bankruptcy. While the O-score uses only accounting variables, Campbell et al. relies on both accounting and market data, especially on the number of firm failures. While Campbell et al. show that their measure can predict corporate failures better than the O-score, their model's results also document a negative relationship between distress risk and equity returns.

The main objective of this study is to explore the contradiction in the finding of a positive distress risk premium in [Vassalou and Xing \(2004\)](#) and the finding of a negative risk premium, i.e., a distress risk discount, in other studies, such as those by [Dichev \(1998\)](#), [Campbell et al. \(2008\)](#), [George and Hwang \(2010\)](#), [Griffin and Lemmon \(2002\)](#), and [Opler and Titman \(1994\)](#). Among the measures used by previous studies, we argue that [Merton's \(1974\)](#) probability of default used by Vassalou and Xing is a more direct measure of distress because firms in financial distress tend to exhibit a higher likelihood of default. This measure allows us to estimate default likelihood indicators for individual firms using equity data instead of relying on default information obtained from accounting data or the bond markets. Also, [Hillegeist et al. \(2004\)](#) show that the Merton model outperforms [Altman's \(1968\)](#) and [Ohlson's \(1980\)](#) models (Z-score and O-score, respectively) with better predictive power. It should also be noted that even though almost five decades have passed since the inception of the [Merton \(1974\)](#) model and several scholars have developed and extended the model even further, the original model is still used widely by a lot of practitioners to assess financial distress ([Afik et al. 2016](#)).

[Vassalou and Xing \(2004\)](#) use [Merton's \(1974\)](#) option pricing model to compute default measures for individual firms and assess the effect of default risk on equity returns during the sample period of 1971–1999. More than two decades have passed since the end of the sample period in Vassalou and Xing. Therefore, it is important to reexamine the contradiction between their findings and the findings of some other studies for the extended period that includes 23 years after their sample period ends in 1999. Specifically, since Vassalou and Xing use the default likelihood indicator computed using the [Merton \(1974\)](#) model, which we argued above to be a more direct measure of distress risk, we examine the extended sample period of 1965–2023 based on Merton's model.

Like the study by [Vassalou and Xing \(2004\)](#), several studies that examine the pricing of default risk in equity returns use a sample period that ends by 2000. The literature on pricing business failure risk in equity valuation has been relatively limited during the past two decades. This period has been tumultuous for the United States, especially with the occurrence of a major terrorist attack, a housing meltdown, a severe economic recession, a significant boom and bust in the U.S. stock market, and a pandemic. Therefore, including this period in the examination of how financial distress risk is priced in equity returns is important.

In this study, to conduct the abovementioned examination for an extended sample period of 1965–2023, we follow [Vassalou and Xing's \(2004\)](#) approach and compute default

likelihood indicators using the contingent claims methodology of [Black and Scholes \(1973\)](#) and [Merton \(1974\)](#). We use the default likelihood indicator as a proxy for financial distress risk.

This study contributes to the literature in multiple ways. It sheds light on the contradiction in the finding of a positive distress risk premium in [Vassalou and Xing \(2004\)](#) and the finding of a negative risk premium, i.e., a distress risk discount, in other studies. It shows that excluding outliers and including the time period beyond the end of Vassalou and Xing's sample period in 1999 both make a difference in the results. Overall, it supports the existence of a distress risk discount. This study is one of the few studies to examine the pricing implication of the financial distress risk factor across a comprehensive sample period, including the past two decades. Also, in this study, we construct an investment strategy that includes information from default likelihood and traditional risk factors like size and BM. We find that this intersection provides additional information different from traditional asset-pricing models. Finally, to our knowledge, this is the first study to examine financial distress risk-pricing implications across economic regimes and the COVID-19 pandemic. It demonstrates that the negative distress risk premium is strong and persistent across expansions, recessions, and the COVID-19 pandemic.

The remainder of the paper is organized as follows: The next section describes the default probability measure used in this study. Section 3 discusses the data and sample construction. Section 4 describes the methodology used for the empirical analysis. Section 5 discusses the findings. The last section contains concluding remarks.

2. Default Probability Measure

Many measures capture the financial distress of a firm. [Dichev \(1998\)](#) finds a negative relationship between stock returns and default probability using [Ohlson's \(1980\)](#) O-score and [Altman's \(1968\)](#) Z-score to proxy for distress risk. He documents that the O-score predicts CRSP delistings better than the Z-score. Because of this, [Griffin and Lemmon \(2002\)](#) focus on the O-score to capture distress risk. Numerous recent studies have also used this measure, including those by [Opler and Titman \(1994\)](#) and [George and Hwang \(2010\)](#). A more recent measure by [Campbell et al. \(2008\)](#) uses a hazard model to predict bankruptcy. While the O-score uses only accounting variables, [Campbell et al. \(2008\)](#) rely on both accounting and market data, especially for the number of firm failures. They show that their measure can predict corporate failures better than the O-score, but the results using this model in asset pricing are consistent with those using the O-score.

The probability of default used by [Merton \(1974\)](#) to capture financial distress seems more direct because firms in financial distress tend to exhibit a higher likelihood of default. This model allows us to estimate default likelihood indicators for individual firms using equity data instead of relying on default information obtained from accounting data or the bond markets. Therefore, we use the default likelihood indicator computed using the [Merton \(1974\)](#) distance-to-default (DD) model popularized by [Vassalou and Xing \(2004\)](#).

According to [Merton's \(1974\)](#) framework, a firm's equity can be considered a call option on the firm's underlying assets. The book value of the firm's debt obligations is the strike price. Within this framework, failure to meet the firm's debt obligations is analogous to letting the call option expire without exercising it. Such a situation may arise when a firm's assets' value is lower than its debt obligations' value.

In the Merton framework, the value of a firm's assets follows a geometric Brownian motion.

$$dV_A = \mu V_A dt + \sigma_A V_A dW \quad (1)$$

where V_A is the value of the firm's assets, μ is the expected return on the firm's assets, σ_A is the volatility of the firm's assets, and dW is a Wiener process. The following equation gives the market value of equity.

$$V_E = V_A N(d_1) - e^{-rT} FN(d_2) \quad (2)$$

where

$$d_1 = \frac{\ln\left(\frac{V_A}{F}\right) + (r + \frac{1}{2}\sigma_A^2)}{\sigma_A\sqrt{T}}$$

$$\text{and } d_2 = d_1 - \sigma_A\sqrt{T}$$

where V_E represents the market value of the firm's equity, F is the face value of the firm's debt obligations, r is the risk-free rate, and $N(\cdot)$ is the cumulative normal distribution. In this framework, the distance to default is calculated as follows.

$$DD = \frac{\ln\left(\frac{V_A}{F}\right) + \left(\mu - \frac{1}{2}\sigma_A^2\right)}{\sigma_A\sqrt{T}} \quad (3)$$

Using the DD measure from the above equation, the expected default probability (EDF) can be measured using the following formula.

$$\text{Default Likelihood} = N(-DD) = N\left(-\left(\frac{\ln\left(\frac{V_A}{F}\right) + \left(\mu - \frac{1}{2}\sigma_A^2\right)}{\sigma_A\sqrt{T}}\right)\right) \quad (4)$$

We follow the methods outlined in [Vassalou and Xing \(2004\)](#) and [Bharath and Shumway \(2008\)](#) to arrive at the empirical measure of default likelihood. To calculate σ_A , we adopt an iterative procedure like Vassalou and Xing. We use daily data from the past 12 months to estimate the volatility of equity, σ_E , which is then used as an initial value for the estimation of σ_A . Using the Black–Scholes formula, and for each trading day of the past 12 months, we compute V_A using V_E as that day's market value of equity. In this manner, we obtain daily values for V_A . We then compute the standard deviation of those V_A 's and use it as the value of σ_A for the next iteration. This procedure is repeated until the values of σ_A from two consecutive iterations converge. This process is repeated at the end of every month, resulting in the estimation of monthly values of σ_A . Once daily values of V_A are estimated, we compute the drift μ by calculating the mean of the change in $\ln(V_A)$. The default likelihood, our measure of financial distress risk, is the probability that the value of the firm's assets will be less than the value of the firm's liabilities.

3. Data and Summary Statistics

The full sample consists of all U.S. firms listed on NYSE, AMEX, and Nasdaq with monthly returns available in the Center for Research in Security Prices (CRSP). Financial firms are excluded from the analysis. The sample period is from November 1965 to December 2023. Accounting data are from the Compustat Annual and Quarterly Industrial Files. Monthly stock return data are from the CRSP database. Specifically, we first collect from CRSP the daily stock returns, price, and share outstanding. We exclude financial firms. We compute the market value of equity as the stock price multiplied by the number of shares outstanding. Then, we collect from Compustat the debt due in one year and long-term debt to create our total debt variable as debt due in one year plus half of long-term debt following [Vassalou and Xing \(2004\)](#). We use monthly observations of the 1-year Treasury Bill rate obtained from the Federal Reserve Board Statistics as the proxy for risk-free rate for the computation of default likelihood. The Fama–French factors HML and SMB, the Carhart factor MOM, and the market factor beta are obtained from Kenneth French's web page. We also obtain data from the same web page for the 1-month T-bill rate used in our asset-pricing tests.

Next, we build our default probability measure. The details of the process are described in the next section. After finding the distance to default and the expected default frequency (i.e., default likelihood indicator) at a monthly frequency, we retrieve from CRSP the monthly stock returns, price, and share outstanding. Then, we retrieve from Compustat the book value of equity and the monthly Fama–French three factors and Carhart factors from Kenneth French's website. Next, we merge the monthly default likelihood data with

our other monthly datasets to obtain a monthly dataset. To avoid potential issues arising from reporting delays, we exclude the book value of debt for the new fiscal year until four months have passed since the end of the previous fiscal year. This ensures that all information used to compute our default likelihood measure was available to the investors at the time of the calculation. Each month, the BM of a firm is the 6-month prior book value of equity divided by the current month's market value of equity. Firms with a negative BM are excluded from our sample.

We conduct an outlier analysis and use a winsorized sample at 5% levels on both tails of returns. Our sample includes 221,944 firm-year observations from 22,189 firms. The average likelihood of default, which is a proxy for average default risk, is 4.36%, and the average return is 0.0054. Note that our average default risk is close to Vassalou and Xing's (2004) average of 4.21% for the period 1971–1999 and below Bharath and Shumway's (2008) average of 10.95% for the period 1980–2003. Table 1 reports the summary statistics.

Table 1. Summary statistics. This table presents summary statistics of firm-year observations for default risk (default likelihood indicator), market capitalization, book-to-market ratio, average return, Fama–French 3-factor return, and Fama–French 4-factor return. Market cap is expressed in millions of dollars. Return is in decimals. Note that the expected default frequency (default likelihood indicator) is a proxy for distress/default risk. Default risk is in percent.

	N	Mean	SD	Median	Min	Max
# of obs.	221,944					
# of firms	22,189					
Default risk		4.3602	14.5543	9.90×10^{-7}	0.0000	100.0000
Market cap		1311.0703	2626.7966	178.112	5.3902	10,412.274
BM		1.0201	1.6941	0.6145	0.0315	13.7485
Return		0.0054	0.1187	0.0000	−0.2202	0.2587
FF3 return		7.97×10^{-12}	0.1096	−0.0031	−0.4224	0.4407
FFC4 return		-2.29×10^{-11}	0.1095	−0.0030	−0.4314	0.4385

4. Methodology

4.1. Default Probability Measure Construction

To build our default probability measure, we first set the value of assets to be equal to the market value of equity plus total debt. We then calculate the initial asset volatility (σ_{A0}) using the standard deviation of daily equity returns. Next, we iteratively estimate the asset value (V_A) and asset volatility (σ_A) using a series of equations derived from the Merton model given above. The iterations continue until the difference between consecutive asset volatility estimates is within a specified tolerance-convergence level of 0.001. Once the convergence level is reached, the values are used to find the distance to default in Equation (3) and default likelihood (expected default frequency) in Equation (4) using the final asset value, the asset volatility, and the expected return on assets (μ). Bharath and Shumway (2006) provide the code for the default risk measure (expected default frequency in their paper and default likelihood indicator) following the method in Vassalou and Xing (2004). We use their SAS code adjusted to our data to build our measure of default. The code we use is provided in Appendix A.

4.2. Default Probability Measure Construction

For this study, we first use the portfolio-sorting approach to examine the relationship between the probability of default, firm size, and firm value on stock returns. We construct three sets of portfolios: single-sorted portfolios based on the probability of default, double-sorted portfolios based on the probability of default and firm size, and double-sorted portfolios based on the probability of default and firm value. For the single-sorted portfolios, at the beginning of each month, we sort all firms into quintiles based on their probability of default and form five equal-weighted and value-weighted portfolios, with quintile 1 containing firms with the lowest probability of default and quintile 5 containing firms

with the highest probability of default. These portfolios are held for one month, and the process is repeated at the beginning of the next month. For the double-sorted portfolios, we independently sort all firms into quintiles based on their probability of default and firm size (measured at the end of the previous month) at the beginning of each month. We then form 25 equal-weighted and value-weighted portfolios by intersecting the probability of default and firm size quintiles. Quintile 1 contains small firms, and quintile 5 contains large firms.

Similarly, for the double-sorted portfolios based on the probability of default and firm value, we independently sort all firms into quintiles based on their probability of default and firm value (measured at the end of the previous month) at the beginning of each month and form 25 equal-weighted and value-weighted portfolios by intersecting the probability of default and firm value quintiles. Quintile 1 contains firms with a low value, and quintile 5 contains firms with a high value. These double-sorted portfolios are also held for one month and rebalanced at the beginning of the next month. Additionally, we calculate abnormal returns using the Fama–French 3-factor and Carhart models. For the Fama–French 3-factor abnormal returns, we regress the excess returns of each portfolio on Fama–French’s 3 factors (market, size, and value) to obtain the portfolio’s abnormal returns (alphas), which represent the portion of the portfolio’s returns not explained by Fama–French’s 3 factors. Similarly, for the Carhart abnormal returns, we regress the excess returns of each portfolio on the Carhart factors (market, size, value, and momentum) to obtain the portfolio’s abnormal returns (alphas), representing the portion of the portfolio’s returns not explained by the Carhart factors.

4.3. Regression Analysis

While the portfolio analysis presents a nonparametric examination of the cross-sectional difference in the relationship between financial distress and stock returns, the regression analysis provides a structural and multivariate view. We carry out our analysis using the methodology of [Fama and MacBeth \(1973\)](#) to investigate the relationship between default risk factor, as measured by the KMV–Merton model, and monthly stock returns, while controlling for Fama–French’s 3 factors (Beta, SMB, and HML) and Carhart’s momentum factor (MOM).

The Fama–MacBeth regression is performed in two steps. First, for each month, a cross-sectional regression of monthly stock returns is run on the estimated default risk factor, along with Fama–French’s 3 factors and Carhart’s momentum factor. The estimated slope coefficients are stored for each month. Second, the time-series averages of the monthly slope coefficients are calculated, representing the overall effect of the default risk factor and the other factors on stock returns across the sample period. The *t*-statistics, which are adjusted for autocorrelation and heteroskedasticity ([Newey and West 1987](#)) for the average slope coefficients are also computed to assess their statistical significance.

5. Empirical Analysis and Findings

In this study, we revisit and confirm prior empirical evidence on returns among financially distressed stocks. Using the likelihood of default computed using [Merton’s \(1974\)](#) option pricing model as a proxy for distress risk, we first construct portfolios of varying levels of distressed stocks. We then perform a regression analysis.

5.1. Single-Sort Portfolio Analysis

Over the sample period of November 1965 to December 2023, at the end of each month, we sort stocks into five portfolios based on their most recently calculated default likelihood. Once the portfolios are formed, each stock is held for one month, and the monthly return is calculated. Table 2 shows the returns statistics of portfolios formed based on default likelihood, including average raw returns, Fama–French three-factor abnormal returns, and Fama–French–Carhart four-factor abnormal returns. Panel A includes the results for equal-weighted portfolios, while Panel B includes the results for value-weighted portfolios.

Table 2. Single-sort portfolio analysis. This table presents the results for the sample from November 1965 to December 2023 of single-sort long–short portfolio analysis based on raw returns, Fama–French (FF) 3-factor returns, and Fama–French–Carhart (FFC) 4-factor returns. The portfolios are sorted based on the probability of default, that is, the default risk. Panel A presents the equal-weighted results, while Panel B presents the value-weighted results.

Panel A: Equal Weighted				
Default Risk	Ave. Default Risk	Average Return	FF3 Return	FFC4 Return
1 (Low)	0.0003	0.0174	0.0125	0.0124
2	0.0836	0.0163	0.0112	0.0111
3	0.3763	0.0114	0.0068	0.0066
4	1.0478	0.0034	−0.0016	−0.0017
5 (High)	24.9805	−0.0205	−0.0255	−0.0257
5-1		−0.0400	−0.0400	−0.0400
<i>t</i> -stat		−21.0436	−21.0440	−21.0440
<i>p</i> -value		0.0000	0.0000	0.0000

Panel B: Value Weighted				
Default Risk	Ave. Default Risk	Average Return	FF3 Return	FFC4 Return
1 (Low)	0.0000	0.0176	0.0126	0.0126
2	0.0011	0.0160	0.0110	0.0109
3	0.0944	0.0109	0.0063	0.0062
4	0.6279	0.0036	−0.0015	−0.0016
5 (High)	13.8112	−0.0113	−0.0164	−0.0165
5-1		−0.0310	−0.0310	−0.0310
<i>t</i> -stat		−12.6877	−12.6878	−12.6878
<i>p</i> -value		0.0000	0.0000	0.0000

In Panel A, the average default risk of the portfolio with the least distressed firms is 0.0003%, whereas it is 24.98% for the portfolio with the most distressed risk. The average raw returns are 1.74% and −2.05% for the least and most distressed firm portfolios, respectively. A long–short portfolio, which is long in the quintile of the most distressed stocks and short in the least distressed stocks, earns about −4% per month. These results show a discount and not a premium associated with financial distress.

The results in the next two columns show that the above returns are not subsumed by the [Fama and French \(1993\)](#) factors or the [Carhart \(1997\)](#) momentum factor. The highest distress portfolio consistently underperforms the lowest distress portfolio. The negative difference in the returns on the portfolios of the most and least distressed firms is similar in all three columns.

We document similar findings in Panel B using value-weighted portfolios. For example, the average raw returns are 1.76% and −1.13% for value-weighted portfolios of the least and most distressed firms, respectively. Our result in Panels A and B of a financial distress discount is inconsistent with that of [Vassalou and Xing \(2004\)](#), who use the same measure as this study, but it is consistent with the other distress risk asset-pricing studies that use different measures.

In the next two subsections, we check the robustness of our findings and explore the possible reasons for our findings differing from those of [Vassalou and Xing \(2004\)](#).

5.2. Subperiod Analysis

[Vassalou and Xing \(2004\)](#) use a sample period that ends in 1999. Our study extends until 2022 and includes more than two additional decades of data. We first conduct a subperiod analysis that matches the Vassalou and Xing sample period from November 1971 to December 1999. So, for this analysis, we do not consider the earlier years of our sample period, 1965–1970. Our second subperiod includes 2000 and beyond, that is, 2000–2023. The results for the first (second) subperiod are reported in Table 3A,B. Panels A and B of both tables include the results for equal-weighted and value-weighted portfolios, respectively.

Table 3. (A) Subsample single-sort portfolio analysis: November 1971–December 1999. This table presents the results of the single-sort long–short portfolio analysis based on raw returns, Fama–French (FF) 3-factor returns, and Fama–French–Carhart (FFC) 4-factor returns for the subperiod 1971–1999. The portfolios are sorted based on the probability of default, that is, the default risk. Panel A presents the equal-weighted results, while Panel B presents the value-weighted results. (B) Subsample single-sort portfolio analysis: 2000–2023. This table presents the results of the single-sort long–short portfolio analysis based on raw returns, Fama–French (FF) 3-factor abnormal returns, and Fama–French–Carhart (FFC) 4-factor abnormal returns for the subperiod 2000–2022. The portfolios are sorted based on the probability of default, that is, the default risk. Panel A presents the equal-weighted results, while Panel B presents the value-weighted results.

(A)			
Panel A: Equal Weighted (1971–1999)			
Default Risk	Average Return	FF3 Return	FFC4 Return
1 (Low)	0.0211	0.0159	0.0159
2	0.0167	0.0118	0.0118
3	0.0121	0.0070	0.0069
4	0.0025	−0.0024	−0.0024
5 (High)	−0.0214	−0.0266	−0.0266
5-1	−0.0411	−0.0411	−0.0411
<i>t</i> -stat	−17.4314	−17.4315	−17.4315
<i>p</i> -value	0.0000	0.0000	0.0000
Panel B: Value Weighted (1971–1999)			
Default Risk	Average Return	FF3 Return	FFC4 Return
1 (Low)	0.0206	0.0154	0.0154
2	0.0163	0.0113	0.0113
3	0.0115	0.0063	0.0063
4	0.0015	−0.0034	−0.0034
5 (High)	−0.0132	−0.0183	−0.0183
5-1	−0.0323	−0.0323	−0.0323
<i>t</i> -stat	−11.4964	−11.4965	−11.4965
<i>p</i> -value	0.0000	0.0000	0.0000
(B)			
Panel A: Equal Weighted (2000–2023)			
Default Risk	Average Return	FF3 Return	FFC4 Return
1 (Low)	0.0144	0.0094	0.0095
2	0.0165	0.0109	0.0109
3	0.0114	0.0064	0.0065
4	0.0038	−0.0018	−0.0018
5 (High)	−0.0218	−0.0273	−0.0272
5-1	−0.0404	−0.0404	−0.0404
<i>t</i> -stat	−14.8378	−14.8379	−14.8379
<i>p</i> -value	0.0000	0.0000	0.0000
Panel B: Value Weighted (2000–2023)			
Default Risk	Average Return	FF3 Return	FFC4 Return
1 (Low)	0.0146	0.0096	0.0097
2	0.0160	0.0104	0.0105
3	0.0117	0.0067	0.0067
4	0.0044	−0.0012	−0.0011
5 (High)	−0.0112	−0.0168	−0.0167
5-1	−0.0301	−0.0301	−0.0301
<i>t</i> -stat	−8.0550	−8.0551	−8.0551
<i>p</i> -value	0.0000	0.0000	0.0000

We first examine Table 3A. We find that, in the first subsample period of 1971–1999, which matches the Vassalou and Xing (2004) sample period, there is a significant difference between portfolios of high- and low-financial-distress firms (Panel A). This is true for raw returns, as well as Fama–French three-factor and Fama–French–Carhart four-factor abnormal returns. In Panels A and B, similar to our findings earlier in Table 2 for the entire sample period, portfolios of firms with high default risk underperform portfolios of firms with low default risk. The difference is statistically significant at the 1% level.

Table 3B shows that the negative relationship between distress risk and equity returns continues for the subsample period after 1999. For 2000–2023, the portfolios consisting of firms with a high default risk significantly underperform portfolios consisting of firms with a low default risk for both equal-weighted and value-weighted portfolios at the 1% level for average raw returns, Fama–French three-factor abnormal returns, and Carhart four-factor abnormal returns.

We examine the possible explanations for the deviation in the results between our study and Vassalou and Xing (2004) during the same period. We observe that Vassalou and Xing use all data without winsorizing, thereby including large outliers in their sample. When we conduct our analysis for a sample including outliers, we find the same results as Vassalou and Xing, whereby the portfolios of firms with high default risk significantly outperform those with low default risk for both equal-weighted and value-weighted portfolios. Therefore, we conclude that our winsorization decision could be one potential reason for our findings to differ from Vassalou and Xing. We also find that our results hold even if we winsorize at the 1%, 2.5%, or 10% level instead of the 5% level used in the results included in the paper. We continue to use winsorized samples in our analysis because our findings align with most distress-risk studies documenting distress risk yielding a discount, not a premium, in equity returns.

5.3. Double-Sort Portfolio Analysis Based on Default Risk and Size

We now sort stocks into 25 groups at the end of each month over the sample period of November 1965 to December 2023. As earlier, we first sort stocks into five portfolios based on their most recently calculated default likelihood. Next, stocks are sorted into five groups independently based on their most recent size proxied by market capitalization. Once the portfolios are formed, each stock is held for one month. We then compute the equal-weighted and value-weighted average raw returns, Fama–French three-factor abnormal returns, and Carhart four-factor abnormal returns for the 25 portfolios based on default risk and size. Table 4A,B report the results for equal-weighted value-weighted portfolios, respectively.

As we move from the leftmost column to the rightmost column, firm size increases monotonically, and returns tend to decrease for default risk quintiles 3 through 5. Thus, for most of the default risk quintile, portfolios with the smaller firms earn a positive risk premium. This is consistent for average raw returns, Fama–French three-factor abnormal returns, and Fama–French–Carhart four-factor abnormal returns across equal-weighted and value-weighted portfolios. This finding from Table 4A,B suggests that the small-size risk factor yields a risk premium. This result about firm size aligns with the established literature on size as a risk factor.

As we move from the topmost row to the bottommost row, default likelihood increases monotonically, and returns decrease in all size quintiles except the lowest size quintile. Thus, as the distress risk increases, returns decrease. This pattern is observed for average raw returns, Fama–French three-factor abnormal returns, and Fama–French–Carhart four-factor abnormal returns across equal-weighted and value-weighted portfolios. We also report the returns on H-L, the long–short portfolio that is long in the quintile with the highest default risk and short in the quintile with the lowest default risk for each size quintile. These returns are negative across all size quintiles. These returns are also statistically significant at the 1% level for each size quintile, except for the lowest size quintile, where they are insignificant. The above results are consistent across average raw returns, Fama–French

three-factor abnormal returns, and Fama–French–Carhart four-factor abnormal returns across equal-weighted and value-weighted portfolios. These results also show that there is a default risk discount.

Table 4. (A) Double-sort equal-weighted portfolio analysis based on default risk and size. This table presents the results of a double-sort equal-weighted portfolio analysis based on the probability of default and market capitalization (default risk and firm size) for the sample period from November 1965 to December 2023. Panel A includes results based on raw returns, Panel B includes results based on Fama–French 3-factor (FF3) returns, and Panel C includes results based on Fama–French–Carhart 4-factor (FFC4) returns. (B) Double-sort value-weighted portfolio analysis based on default risk and size. This table presents the results of a double-sort value-weighted portfolio analysis based on the probability of default and market capitalization (default risk and firm size) for the sample period from November 1965 to December 2023. Panel A includes results based on raw returns, Panel B includes results based on Fama–French 3-factor (FF3) returns, and Panel C includes results based on Fama–French–Carhart 4-factor (FFC4) returns.

(A)					
Panel A: Average Returns					
	Default Risk			Size	
	1 (Small)	2	3	4	5 (Big)
1 (Low)	0.0030	0.0163	0.0198	0.0213	0.0206
2	−0.0015	0.0119	0.0193	0.0198	0.0192
3	−0.0083	0.0088	0.0148	0.0176	0.0181
4	−0.0191	−0.0003	0.0080	0.0132	0.0144
5 (High)	−0.0445	−0.0219	−0.0103	−0.0038	0.0033
5-1	−0.0471	−0.0367	−0.0303	−0.0250	−0.0163
<i>t</i> -stat	−30.4450	−21.1766	−15.7135	−14.5279	−9.2897
<i>p</i> -value	0.0000	0.0000	0.0000	0.0000	0.0000
Panel B: FF3 Abnormal Returns					
	Default Risk			Size	
	1 (Small)	2	3	4	5 (Big)
1 (Low)	−0.0019	0.0112	0.0152	0.0163	0.0155
2	−0.0065	0.0069	0.0142	0.0147	0.0142
3	−0.0133	0.0040	0.0100	0.0128	0.0134
4	−0.0242	−0.0054	0.0029	0.0082	0.0093
5 (High)	−0.0492	−0.0265	−0.0151	−0.0084	−0.0014
5-1	−0.0471	−0.0367	−0.0303	−0.0250	−0.0163
<i>t</i> -stat	−30.4450	−21.1768	−15.7136	−14.5280	−9.2898
<i>p</i> -value	0.0000	0.0000	0.0000	0.0000	0.0000
Panel C: FFC4 Abnormal Returns					
	Default Risk			Size	
	1 (Small)	2	3	4	5 (Big)
1 (Low)	−0.0020	0.0111	0.0150	0.0162	0.0154
2	−0.0066	0.0068	0.0141	0.0146	0.0141
3	−0.0134	0.0039	0.0098	0.0127	0.0133
4	−0.0243	−0.0055	0.0028	0.0081	0.0092
5 (High)	−0.0493	−0.0266	−0.0152	−0.0085	−0.0015
5-1	−0.0471	−0.0367	−0.0303	−0.0250	−0.0163
<i>t</i> -stat	−30.4450	−21.1768	−15.7136	−14.5280	−9.2898
<i>p</i> -value	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4. Cont.

(B)					
Panel A: Average Return					
	Default Risk			Size	
	1 (Small)	2	3	4	5 (Big)
1 (Low)	0.0049	0.0171	0.0200	0.0211	0.0198
2	0.0003	0.0126	0.0197	0.0198	0.0183
3	−0.0067	0.0092	0.0147	0.0176	0.0169
4	−0.0175	−0.0002	0.0078	0.0132	0.0131
5 (High)	−0.0424	−0.0211	−0.0100	−0.0035	0.0030
5-1	−0.0471	−0.0368	−0.0303	−0.0245	−0.0158
<i>t</i> -stat	−29.4823	−20.4890	−15.5301	−13.9200	−8.3350
<i>p</i> -value	0.0000	0.0000	0.0000	0.0000	0.0000
Panel B: FF3 Abnormal Returns					
	Default Risk			Size	
	1 (Small)	2	3	4	5 (Big)
1 (Low)	0.0000	0.0120	0.0154	0.0161	0.0147
2	−0.0047	0.0075	0.0147	0.0147	0.0132
3	−0.0117	0.0043	0.0099	0.0128	0.0122
4	−0.0225	−0.0053	0.0027	0.0082	0.0080
5 (High)	−0.0471	−0.0257	−0.0148	−0.0081	−0.0016
5-1	−0.0471	−0.0368	−0.0303	−0.0245	−0.0158
<i>t</i> -stat	−29.4823	−20.4891	−15.5301	−13.9201	−8.3351
<i>p</i> -value	0.0000	0.0000	0.0000	0.0000	0.0000
Panel C: FFC4 Abnormal Returns					
	Default Risk			Size	
	1 (Small)	2	3	4	5 (Big)
1 (Low)	−0.0001	0.0120	0.0153	0.0160	0.0146
2	−0.0048	0.0074	0.0146	0.0146	0.0131
3	−0.0118	0.0042	0.0097	0.0127	0.0121
4	−0.0226	−0.0053	0.0026	0.0081	0.0079
5 (High)	−0.0472	−0.0259	−0.0149	−0.0082	−0.0017
5-1	−0.0471	−0.0368	−0.0303	−0.0245	−0.0158
<i>t</i> -stat	−29.4823	−20.4891	−15.5301	−13.9201	−8.3351
<i>p</i> -value	0.0000	0.0000	0.0000	0.0000	0.0000

5.4. Double-Sort Portfolio Analysis Based on Default Risk and the Book-to-Market Ratio

In this subsection, we perform a double-sort analysis based on default risk and the book-to-market ratio. So, as in the previous subsection, we first sort stocks into five portfolios at the end of each month over the sample period of November 1965 to December 2023, based on their most recently calculated default likelihood. Next, stocks are sorted into five groups, independently, based on their most recent book-to-market ratio (BM). Once the portfolios are formed, each stock is held for one month. We then compute the equal-weighted and value-weighted returns over the next month.

Table 5A,B present the average raw returns, Fama–French three-factor abnormal returns, and Carhart four-factor abnormal returns for equal-weighted and value-weighted portfolios, respectively. We also report the returns on H-L, the long–short portfolio that is long in the quintile with the highest default risk and short in the quintile with the lowest default risk for each BM quintile.

In both Table 5A,B, as we move from the leftmost column to the rightmost column, BM increases monotonically, and returns decrease. A lower BM indicates growth firms, and a higher BM indicates value firms. Also, as we move from the topmost row to the bottom row, default likelihood increases monotonically, and returns decrease in all BM quintiles except for the lowest quintile in Table 5A.

The above findings imply that portfolios consisting of value firms with high default risk underperform portfolios consisting of growth firms. This is consistent for average raw returns, Fama–French three-factor abnormal returns, and Carhart four-factor abnormal returns across equal-weighted and value-weighted portfolios. We conclude that the BM is a risk factor yielding a premium, as established in prior asset-pricing literature (Fama and French 1992). We also report the H-L, the long–short portfolio that is long in the highest and short in the lowest quintile of financial distress. We find that (high–low) distress returns are negative and statistically significant for all BM portfolios except for the lowest quintile. These results are consistent across equal-weighted and value-weighted portfolios and irrespective of the type of returns, including average raw returns, Fama–French three-factor abnormal returns, and Carhart four-factor abnormal returns. These results show again that there is a default risk discount.

Table 5. (A) Double-sort equal-weighted portfolio analysis based on default risk and BM. This table presents the results of double-sort equal-weighted portfolio analysis based on the probability of default and the book-to-market ratio (default risk and BM) for the sample period from November 1965 to December 2023. Panel A includes results based on raw returns, Panel B includes results based on Fama–French 3-factor (FF3) returns, and Panel C includes results based on Fama–French–Carhart 4-factor (FFC4) returns. (B) Double-sort value-weighted portfolio analysis based on default risk and BM. This table presents the results of a double-sort value-weighted portfolio analysis based on the probability of default and the book-to-market ratio (default risk and BM) for the sample period from November 1965 to December 2023. Panel A includes results based on raw returns, Panel B includes results based on Fama–French 3-factor (FF3) returns, and Panel C includes results based on Fama–French–Carhart 4-factor (FFC4) returns.

(A)					
Panel A: Average Return					
	Default Risk			Book-to-Market Ratio	
	1 (Low)	2	3	4	5 (High)
1 (Low)	0.0248	0.0192	0.0147	0.0091	0.0022
2	0.0269	0.0193	0.0135	0.0089	−0.0022
3	0.0277	0.0185	0.0104	0.0046	−0.0099
4	0.0209	0.0135	0.0075	−0.0008	−0.0204
5 (High)	0.0013	−0.0008	−0.0076	−0.0172	−0.0437
5-1	−0.0252	−0.0191	−0.0221	−0.0257	−0.0459
<i>t</i> -stat	−12.9714	−10.7868	−12.1276	−13.4838	−23.6286
<i>p</i> -value	0.0000	0.0000	0.0000	0.0000	0.0000
Panel B: FF3 Abnormal Returns					
	Default Risk			Book-to-Market Ratio	
	1 (Low)	2	3	4	5 (High)
1 (Low)	0.0198	0.0140	0.0096	0.0039	−0.0030
2	0.0219	0.0141	0.0082	0.0037	−0.0074
3	0.0221	0.0132	0.0054	−0.0007	−0.0148
4	0.0160	0.0083	0.0022	−0.0060	−0.0256
5 (High)	−0.0037	−0.0056	−0.0124	−0.0221	−0.0485
5-1	−0.0252	−0.0191	−0.0221	−0.0257	−0.0459
<i>t</i> -stat	−12.9715	−10.7869	−12.1277	−13.4837	−23.6287
<i>p</i> -value	0.0000	0.0000	0.0000	0.0000	0.0000
Panel C: FFC4 Abnormal Returns					
	Default Risk			Book-to-Market Ratio	
	1 (Low)	2	3	4	5 (High)
1 (Low)	0.0197	0.0139	0.0095	0.0038	−0.0031
2	0.0218	0.0140	0.0081	0.0036	−0.0075
3	0.0221	0.0131	0.0053	−0.0008	−0.0149
4	0.0159	0.0081	0.0021	−0.0061	−0.0257
5 (High)	−0.0038	−0.0057	−0.0125	−0.0221	−0.0485
5-1	−0.0252	−0.0191	−0.0221	−0.0257	−0.0459
<i>t</i> -stat	−12.9715	−10.7869	−12.1277	−13.4837	−23.6287
<i>p</i> -value	0.0000	0.0000	0.0000	0.0000	0.0000

Table 5. Cont.

(B)					
Panel A: Average Return					
	Default Risk			Book-to-Market Ratio	
	1 (Low)	2	3	4	5 (High)
1 (Low)	0.0211	0.0176	0.0150	0.0108	0.0074
2	0.0248	0.0174	0.0129	0.0076	0.0016
3	0.0265	0.0160	0.0094	0.0046	−0.0068
4	0.0195	0.0112	0.0050	−0.0017	−0.0190
5 (High)	0.0077	0.0024	−0.0051	−0.0134	−0.0329
5-1	−0.0146	−0.0143	−0.0199	−0.0236	−0.0403
<i>t</i> -stat	−6.0614	−6.5059	−8.3026	−9.6858	−15.2679
<i>p</i> -value	0.0000	0.0000	0.0000	0.0000	0.0000
Panel B: FF3 Abnormal Returns					
	Default Risk			Book-to-Market Ratio	
	1 (Low)	2	3	4	5 (High)
1 (Low)	0.0161	0.0124	0.0099	0.0056	0.0022
2	0.0198	0.0122	0.0077	0.0024	−0.0035
3	0.0209	0.0107	0.0044	−0.0006	−0.0117
4	0.0146	0.0060	−0.0002	−0.0069	−0.0241
5 (High)	0.0027	−0.0024	−0.0100	−0.0182	−0.0377
5-1	−0.0146	−0.0143	−0.0199	−0.0236	−0.0403
<i>t</i> -stat	−6.0614	−6.5061	−8.3025	−9.6858	−15.2680
<i>p</i> -value	0.0000	0.0000	0.0000	0.0000	0.0000
Panel C: FFC4 Abnormal Returns					
	Default Risk			Book-to-Market Ratio	
	1 (Low)	2	3	4	5 (High)
1 (Low)	0.0160	0.0123	0.0098	0.0055	0.0021
2	0.0197	0.0121	0.0076	0.0023	−0.0036
3	0.0209	0.0107	0.0043	−0.0007	−0.0118
4	0.0145	0.0059	−0.0003	−0.0070	−0.0242
5 (High)	0.0027	−0.0025	−0.0100	−0.0183	−0.0377
5-1	−0.0146	−0.0143	−0.0199	−0.0236	−0.0403
<i>t</i> -stat	−6.0614	−6.5061	−8.3025	−9.6858	−15.2680
<i>p</i> -value	0.0000	0.0000	0.0000	0.0000	0.0000

5.5. Regression Analysis

We now turn to a regression analysis to further examine the evidence we have presented thus far. The results of Fama–MacBeth regressions are provided in Table 6. The independent variables in these regressions include default risk and either three or four factors, including the market factor (beta), the Fama–French factors (SMB and HML), and the Carhart factor (MOM). These factors are obtained from Kenneth French’s web page.

We find that, in the first model, which includes Fama–French’s three risk factors—beta, size, and BM—the distress premium is negative and statistically significant. We also confirm the consistency of the negative relationship between default likelihood and returns using Fama–French–Carhart’s four factors—beta, size, BM, and momentum—as independent variables in the second model. BM is significant in the Fama–French three-factor regression, indicating that the information contents of these two variables (BM and default likelihood) are orthogonal to each other, and they both represent important firm-specific risk factors.

5.6. Distress Risk and Equity Returns across Economic Regimes

In this subsection, we focus on the relationship between default risk and equity returns during expansionary versus recessionary periods of the U.S. business cycle. Assigning each month of our sample period to either the recessionary or expansionary portion of the business cycle helps us analyze whether a good-versus-bad economic climate affects the relationship between default risk and returns. We use the U.S. Business Cycle Expansions and Contractions data from the National Bureau of Economic Research (NBER). The recessionary period goes from peak to trough, while the expansionary period goes from

trough to peak. With the COVID-19 pandemic period being unique, we also examine this period separately. In accordance the World Health Organization, we consider January 2020 to be the pandemic's start. So, the pandemic period in our sample consists of January 2020–December 2023 (the end of our sample period).

Table 6. Fama–MacBeth regressions. This table presents the Fama–MacBeth regression results for the sample period from November 1965 to December 2023, with returns as the dependent variable. We include results for both the Fama–French 3-factor and Fama–French–Carhart 4-factor models. In column 1, we regress on default risk, market beta, size, value, and momentum. In column 2, we regress on default risk, market beta, size, value, and momentum. The *t*-statistics are reported in parentheses below the coefficients. The coefficient and the *t*-statistic for the main variable of interest are in bold.

	Fama–French 3	Fama–French–Carhart 4
Default risk	−0.0009 (−10.0700)	−0.0009 (−9.9700)
Market (beta)	0.6604 (6.3900)	0.6390 (3.0000)
Size (SMB)	0.6322 (4.9400)	0.3165 (1.0000)
Value (HML)	0.3717 (2.0700)	0.1230 (0.3500)
Momentum (MOM)		0.2732 (0.9300)
Intercept	0.0011 (0.4500)	−0.0023 (−0.5200)
R-squared	0.1042	0.1062

Table 7A,B present the average raw returns, Fama–French three-factor abnormal returns, and Fama–French–Carhart four-factor abnormal returns for equal-weighted and value-weighted portfolios, respectively. Furthermore, we compute the returns for (high–low), the long–short portfolio that is long in the least quintile and short in the highest quintile of the default likelihood.

Panel A of the above tables presents the results for the expansionary periods. Panels B and C present the results for the recessionary periods and the COVID-19 pandemic, respectively. We find in Panel A that for portfolios sorted on default likelihood during expansionary periods, portfolios consisting of firms with high default risk underperform portfolios consisting of firms with low default risk. The difference in performance is statistically significant at the 1% level. This is consistent across average raw returns, Fama–French three-factor abnormal returns, and Fama–French–Carhart four-factor abnormal returns for both equal-weighted and value-weighted portfolios. In Panels B and C that report results for the recessionary periods and during the pandemic, portfolios consisting of firms with high default risk underperform portfolios consisting of firms with low default risk. We also find that the difference in performance is statistically significant for the recessionary and pandemic periods.

We acknowledge that these portfolio returns are merely a nonparametric examination of the cross-sectional differences in the relationship between distress risk and stock returns. A regression analysis provides a structural and multivariate view of this cross-sectional relationship. So, as presented in Section 5.5, we conduct Fama and MacBeth (1973) regressions across the expansionary, recessionary, and COVID-19 pandemic periods. In our analysis, month $t + 1$ return is the dependent variable, and the independent variables are for month t and include characteristics known to affect returns. These independent variables include beta, book-to-market ratio, momentum measured by past 6-month returns, and size captured by equity market capitalization. The results of the Fama–MacBeth regressions are shown in Table 8.

Table 7. (A) Subsample single-sort equal-weighted portfolio analysis. This table presents the results of a single-sort long–short equal-weighted portfolio analysis based on raw returns, Fama–French (FF) 3-factor returns, and Fama–French–Carhart (FFC) 4-factor returns during expansionary, recessionary, and COVID-19 pandemic periods. The portfolios are sorted based on the probability of default, that is, the default risk. Panels A and B present the results for expansionary and recessionary periods, respectively. Panel C presents the results for the COVID-19 pandemic period. (B) Subsample single-sort value-weighted portfolio analysis. This table presents the results of single-sort long–short value-weighted portfolio analysis based on raw returns, Fama–French (FF) 3-factor returns, and Fama–French–Carhart (FFC) 4-factor returns during expansionary, recessionary, and COVID-19 pandemic periods. The portfolios are sorted based on the probability of default, that is, the default risk. Panels A and B present results for expansionary and recessionary periods, respectively. Panel C presents the results for the COVID-19 pandemic period.

(A)			
Panel A: Expansionary periods			
Default Risk	Average Return	FF3 Return	FFC4 Return
1 (Low)	0.0173	0.0120	0.0119
2	0.0163	0.0110	0.0109
3	0.0118	0.0068	0.0067
4	0.0039	−0.0013	−0.0014
5 (High)	−0.0195	−0.0248	−0.0249
5-1	−0.0393	−0.0393	−0.0393
<i>t</i> -stat	−19.5241	−19.5245	−19.5245
<i>p</i> -value	0.0000	0.0000	0.0000
Panel B: Recessionary periods			
Default Risk	Average Return	FF3 Return	FFC4 Return
1 (Low)	0.0181	0.0162	0.0162
2	0.0162	0.0131	0.0131
3	0.0083	0.0068	0.0068
4	−0.0003	−0.0034	−0.0034
5 (High)	−0.0272	−0.0303	−0.0303
5-1	−0.0447	−0.0447	−0.0447
<i>t</i> -stat	−8.0085	−8.0086	−8.0086
<i>p</i> -value	0.0000	0.0000	0.0000
Panel C: COVID-19 pandemic period			
Default Risk	Average Return	FF3 Return	FFC4 Return
1 (Low)	0.0134	0.0122	0.0123
2	0.0157	0.0126	0.0127
3	0.0119	0.0089	0.0089
4	−0.0011	−0.0041	−0.0041
5 (High)	−0.0300	−0.0331	−0.0330
5-1	−0.0501	−0.0501	−0.0501
<i>t</i> -stat	−6.4108	−6.4108	−6.4108
<i>p</i> -value	0.0000	0.0000	0.0000
(B)			
Panel A: Expansionary periods			
Default Risk	Average Return	FF3 Return	FFC4 Return
1 (Low)	0.0174	0.0121	0.0120
2	0.0164	0.0111	0.0110
3	0.0112	0.0062	0.0061
4	0.0037	−0.0015	−0.0016
5 (High)	−0.0108	−0.0161	−0.0162
5-1	−0.0307	−0.0307	−0.0307
<i>t</i> -stat	−12.1834	−12.1836	−12.1836
<i>p</i> -value	0.0000	0.0000	0.0000

Table 7. *Cont.*

Panel B: Recessionary periods			
Default Risk	Average Return	FF3 Return	FFC4 Return
1 (Low)	0.0187	0.0168	0.0168
2	0.0137	0.0106	0.0106
3	0.0085	0.0071	0.0071
4	0.0025	−0.0006	−0.0006
5 (High)	−0.0147	−0.0179	−0.0179
5-1	−0.0329	−0.0329	−0.0329
<i>t</i> -stat	−4.1348	−4.1348	−4.1348
<i>p</i> -value	0.0001	0.0001	0.0001
Panel C: COVID-19 pandemic period			
Default Risk	Average Return	FF3 Return	FFC4 Return
1 (Low)	0.0156	0.0144	0.0145
2	0.0175	0.0145	0.0145
3	0.0150	0.0120	0.0120
4	0.0062	0.0032	0.0032
5 (High)	−0.0080	−0.0111	−0.0110
5-1	−0.0304	−0.0304	−0.0304
<i>t</i> -stat	−3.0513	−3.0513	−3.0513
<i>p</i> -value	0.0044	0.0044	0.0044

Table 8. Fama–MacBeth regression analysis. This table presents the Fama–MacBeth regressions’ results with returns as the dependent variable during the expansionary, recessionary, and COVID-19 pandemic periods. We include results for both the Fama–French 3-factor (column 1) and Fama–French–Carhart 4-factor (column 2) models. In column 1, we regress returns on default risk, market beta, size, and value. In column 2, we regress returns on the above three factors and momentum. Panels A and B present the results for expansionary and recessionary periods, respectively. Panel C presents the results for the COVID-19 pandemic period. The *t*-statistics are reported in parentheses below the coefficients. The coefficient and the *t*-statistic for the main variable of interest are in bold.

Panel A: Expansionary Periods	(1)	(2)
Default risk	−0.0009 (−9.9700)	−0.0009 (−9.8700)
Market (beta)	0.7078 (5.9100)	0.5635 (2.2900)
Size (SMB)	−0.0015 (−0.0000)	0.0600 (0.1700)
Value (HML)	0.2174 (0.7900)	0.1541 (0.3600)
Momentum (MOM)		0.3165 (0.9400)
Intercept	0.0261 (1.2400)	0.0114 (1.6900)
<i>R</i> -squared	0.0882	0.0899
Panel B: Recessionary periods	(1)	(2)
Default risk	−0.0008 (−4.0900)	−0.0009 (−4.1100)
Market (beta)	−0.7807 (−0.3900)	−1.4340 (−0.6500)
Size (SMB)	5.3366 (1.3800)	8.1186 (1.4400)
Value (HML)	1.7831 (0.5600)	−3.8937 (−0.4300)
Momentum (MOM)		1.2719 (0.6800)
Intercept	−0.0473 (−0.4700)	−0.1885 (−1.8100)
<i>R</i> -squared	0.1121	0.1131

Table 8. Cont.

Panel C: COVID-19 pandemic period	(1)	(2)
Default risk	−0.0008 (−6.6300)	−0.0008 (−6.5400)
Market (beta)	0.9700 (1.7300)	1.2183 (1.9900)
Size (SMB)	1.5576 (1.7800)	1.6029 (0.7800)
Value (HML)	0.0988 (0.7400)	−0.0218 (−0.0400)
Momentum (MOM)		1.7599 (2.0300)
Intercept	−0.0020 (−0.2800)	−0.0553 (−2.8600)
R-squared	0.1733	0.1768

We find that default risk has a significant negative relationship with equity returns during all economic regimes and across all specifications. Distress premium is negative and statistically significant across expansionary, recessionary, and COVID-19 pandemic periods in both the Fama–French three-factor and Fama–French–Carhart four-factor model specifications. Our findings from the Fama–MacBeth portfolio analysis align with those of the portfolio analysis.

6. Conclusions

Firms are exposed to financial risk arising from the uncertainty of a company's ability to pay off its debt obligations. The prior literature examines risk premiums associated with financial risk in equity returns and finds conflicting results. Few studies find that returns are higher for high-distress-risk firms than for low-distress-risk firms yielding a distress risk premium, while most studies find distress risk to yield a discount instead of a premium.

In this study, we reexamine the above issue for an extended sample period of 1965–2023. We use Merton's (1974) probability of default for this examination, as this is a more direct measure of financial distress. It also allows us to estimate default likelihood indicators using equity data instead of relying on information about default obtained from accounting data or the bond markets.

We first sort stocks into five portfolios (quintiles) at the end of each month based on their most recently calculated default likelihood. Each stock is held for one month, and the monthly return is calculated. We find that a portfolio long in the quintile of the most distressed stocks and short in the least distressed stocks earns a significant negative return per month. This finding is consistent across average raw returns, Fama–French three-factor abnormal returns, and Fama–French–Carhart four-factor abnormal returns, and for both equal-weighted portfolios. These results imply a discount and not a premium associated with financial distress.

The above implication for the entire sample period of November 1965–December 2023 is inconsistent with Vassalou and Xing (2004), who use the same measure as this study, but is consistent with the other distress risk asset-pricing studies that use different measures. We conduct a subperiod analysis to explore further the inconsistency of our results with those of Vassalou and Xing. In this analysis, we separately examine subperiods of 1971–1999 and 2000–2023. The first subperiod matches that of Vassalou and Xing.

For the first subperiod, we find a significant difference between equal-weighted portfolios of high and low financial distress firms. We find a financial distress discount for value-weighted portfolios. We examine the possible reason for the difference in results between our study and Vassalou and Xing (2004) during the same period. We observe that Vassalou and Xing use all data without winsorizing, thereby including large outliers in their sample. When we analyze our sample without excluding outliers, we find the

same results as Vassalou and Xing, whereby portfolios of firms with high default risk significantly outperform those with low default risk for both equal-weighted and value-weighted portfolios. To avoid biases caused by large outliers, we continue to use winsorized samples for our study.

For the second subperiod of 2000–2023, we find a strong negative relationship between distress risk and equity returns. The portfolios consisting of firms with high default risk significantly underperform portfolios consisting of firms with low default risk for both equal-weighted and value-weighted portfolios at the 1% significance level for average raw returns, Fama–French three-factor abnormal returns, and Carhart four-factor abnormal returns. These results support the presence of a distress risk discount, termed a distress risk anomaly, since it is not supported by rational asset-pricing theory.

Next, we examine the extent of this financial distress risk's overlap with “small-minus-big” (size) or “high-minus-low” (value) risk that is commonly used in standard equity risk assessments. Although, in isolation, size and value have risk premiums (for small and growth firms), it is important to examine the interaction between them and financial distress. We empirically test the interaction by constructing a two-dimensional investment strategy with size and default likelihood and then similarly with BM and default likelihood. Consistent with the prior literature, we find a risk premium associated with small and growth firms. More importantly for this study, we find that, except for the lowest size and BM quintiles, portfolios long in the quintile with the highest default risk and short in the quintile with the lowest default risk have significantly negative returns for each size (BM) quintile. This finding further confirms the presence of a default risk discount even after accounting for size and BM risk factors.

We realize that portfolio analysis presents a nonparametric examination of the cross-sectional difference in the relationship between financial distress and stock returns. A regression analysis is needed for a structural and multivariate view of this cross-sectional difference. Therefore, we further conduct a regression analysis. We use the methodology of [Fama and MacBeth \(1973\)](#) for this purpose. In our separate regression models, including the Fama–French three factors and Fama–French–Carhart four factors, we find that the coefficient of the distress risk measure (default likelihood) is negative and statistically significant. Thus, our regression results are consistent with our results based on portfolio single and double sorts.

We also analyze whether a good-versus-bad economic climate affects the default risk and return relationship. For this purpose, we analyze this relationship separately for expansionary versus recessionary periods of the U.S. business cycle. In addition, we also examine the relationship specifically for the COVID-19 pandemic period. We document that, during the expansionary, recessionary, and pandemic periods, portfolios of firms with high default risk underperform those with low default risk. Upon further examination using Fama–MacBeth regressions, we document that default risk is negative and statistically significant across all subperiods, i.e., expansionary, recessionary, and the COVID-19 pandemic.

The default discount highlights the importance of effective risk management practices for investors, financial institutions, and regulators. Policymakers should encourage the development and adoption of robust risk assessment and management frameworks to mitigate the impact of default risk on the financial system.

There are several avenues for future research. In this study, we find that the exclusion of outliers affects the results. It would be interesting to examine this issue in more detail. It would also be interesting to examine how the default discount varies across industries during different time periods. For example, during the COVID-19 pandemic, the hospitality and travel industries were highly adversely affected by the restrictions imposed during that period, whereas several sectors of the technology industry experienced exceptional growth. It would be interesting to examine how the financial distress discount varied across these industries during the abovementioned period.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

SAS Code for the default measure: [Bharath and Shumway’s paper \(2006\)](#), which is the working paper version of [Bharath and Shumway \(2008\)](#), has the code for the default risk measure following [Vassalou and Xing \(2004\)](#). We use their SAS code and adjust it to our data to build our measure. The code is provided below.

```
data work.CCM;
    set "C:\Users\konen\Downloads\Sas May 24\CCM.sas7bdat";
run;

data work.RF;
    set "C:\Users\konen\Downloads\Sas May 24\RF.sas7bdat";
run;

data work.dailycrsp1;
    set "C:\Users\konen\Downloads\Sas May 24\dailycrsp.sas7bdat";
run;

data rf1;
    set rf;

    /* Create year and month variables from the date variable */
    year = year(dateff);
    month = month(dateff);

    /* Drop the original date variable */
    drop dateff;
run;

proc sort data = rf1 nodupkey out = rf1;
    by year month;
run;

data ccm1;
    set ccm;

    /* Create year and month variables from the date variable */
    permno = lpermno;
    year = year(datadate);
    month = month(datadate);

run;
```

```

/* Sort the 'ccm1' dataset by year and month */
proc sort data = ccm1;
    by year month;
run;

/* Merge the 'ccm1' and 'rf1' datasets by year and month, dropping non-merged observations */
data ccm1;
    merge ccm1(in = a) rf1(in = b);
    by year month;
    if a and b;
    r = rf;
run;

proc sort data = ccm1 nodupkey; by permno datadate; run;

data ccm2;
    set ccm1;
    by permno datadate;
    /* remove firms with only one quarter's observation */
    if not (first.permno and last.permno);
    /* replace missing debt with 0 */
    if missing(dd1q) then dd1q = 0;
    if missing(dl1ttq) then dl1ttq = 0;
    /* align date to quarter-end date */
    qtrdate = intnx('quarter', datadate, 0, 'e');
    format qtrdate date9.;

run;

proc sort data = ccm2 nodupkey; by permno qtrdate; run;
proc expand data = ccm2 out = temp from = qtr to = month;
    id qtrdate; by permno;
    convert permno dd1q dl1ttq/method = step;
run;

%let year_start = 1963;
%let year_end = 2024;

proc sql;
    /* COMP dataset: risk-free rate and face value of debt */
    create table comp as
    select a.permno,
        /* align to month-end */
        intnx('month', a.qtrdate, 0, 'e') as cdt format = date9.,
        /* monthly risk-free rate (1-month Treasury Bill) */
        b.rf as r1 label = "risk-free rate",
        /* face value of debt
        "Following Vassalou and Xing (2004), we take F,
        the face value of debt, to be debt due in one year
        plus one-half of longterm debt." */
        1000*(a.dd1q + 0.5 * a.dl1ttq) as f label = "face value of debt"
    from temp as a, rf as b

```

```

where
    calculated cdt = b.dateff and not missing(b.rf)
    and (&year_start. <= year(calculated cdt) <= &year_end.)
order by permno, cdt;
quit;

proc sql;
/* CRSP dataset: market value of equity */
create table crsp as
select permno, date,
/* market value of equity */
abs(prc)*shrout as e label = "market value of equity",
/* align date to month-end */
intnx('month', date, 0, 'e') as cdt format = date9.
from dailycrsp1(keep = permno date shrout prc)
where
/* extend by 1yr to allow for rolling window */
(&year_start.-1 <= year(date) <= &year_end.);
quit;
data kmv; curdat = 0;
%macro itera(yyy,mmm);
proc sql;
/* COMP-CRSP merged sample, past-12m data for each firm */
/* placed inside the macro to reduce disk requirement */
create table sample as
select
    comp.*, crsp.date, crsp.e,
    (crsp.e+comp.f) as a label = "market value of assets"
from comp, crsp
where
    year(comp.cdt)=&yyy. and month(comp.cdt)=&mmm. and
    crsp.permno=comp.permno and not missing(crsp.permno)
    and crsp.cdt between intnx('year',comp.cdt,-1) and comp.cdt
order by comp.permno, comp.cdt, crsp.date;
quit;

/* Get volatility of total asset returns and equity returns */
data one; set sample; by permno;
    ra = log(a/lag1(a)); re = log(e/lag1(e));
    if first.permno then do ra = .; re = .; end;
    if f > 0 and e ne . and a ne . and permno ne . and e ne 0;
run;

/* Get init value of VA, sigma_E * E/(E+F) as stated in the paper */
proc means noprint data=one; var ra re f e; by permno; output out=bob;
data bob1(keep=permno va); set bob;
    if _stat_ = 'STD' and _freq_ >= 50;
/* here 're' is the std.dev of equity return */
/* later we multiply E/A */
va = sqrt(252) * re;
data bob2(keep=permno largev); set bob;
    if _stat_ = 'MEAN';
    if f > 100,000 and e > 100,000 then largev = 1; else largev = 0;

data one; merge one bob1 bob2; by permno;
/* note a side-effect here:
    (e/a) is varying daily, and so is va as a result */

```

```

    va = va * (e/a);
    if va < 0.01 then va = 0.01;
    if va = . then delete;
    if largev = 1 then do; f = f/10,000; e = e/10,000; a = a/10,000; end;
    drop ra;
run;

data conv; permno = 0;

* iteration;
%do j = 1 %to 15;
    dm 'log;clear;';
    ods _all_ close;
    ods listing close;

    proc model noprint data = one;
        endogenous a;
        exogenous r1 f va e;
        e = a*probnorm((log(a/f) + (r1+va*va/2))/va)
            - f*exp(-r1)*probnorm((log(a/f) + (r1-v*va/2))/va);
        solve a/out = two;

    data two; set two; num = _n_; keep a num;
    data one; set one; num = _n_; drop a;
    data two; merge one two; by num; l1p = lag1(permno); l1a = lag1(a);
    data two; set two; if l1p = permno then ra = log(a/l1a);
    proc means noprint data = two; var ra; by permno; output out = bob;
    data bar; set bob; if _stat_ = 'MEAN'; mu = 252*ra; keep permno mu;
    data bob; set bob; if _stat_ = 'STD'; va1 = sqrt(252)*ra;
        if va1 < 0.01 then va1 = 0.01; keep permno va1;
    data one; merge two bob bar; by permno; vdif = va1 - va;
        if abs(vdif) < 0.001 and vdif ne . then do; conv = 1; end;
    data fin; set one; if conv = 1; assetvol = va1;
    proc sort; by permno descending date;
    data fin; set fin; if permno ne lag1(permno); curdat = 100*&yyy + &mmm; iter = &j;
    data conv; merge conv fin; by permno; drop va re ra l1p l1a conv cdt num;
    data one; set one; if conv ne 1; va = va1; drop va1;
%end;

data kmv; merge kmv conv; by curdat;
    DD=((log(a/f) + (mu-(assetvol**2)/2))/assetvol);
    edf = 100 * probnorm(-(log(a/f) + (mu-(assetvol**2)/2))/assetvol));

    if permno = 0 or curdat = 0 then delete; drop va1;
    label edf = 'expected default frequency';
    label curdat = 'date in yyyy-mm format';
    label e = 'market equity';
    label iter = 'iterations required';
    label assetvol = 'volatility of a';
    label f = 'debt due in one year + 0.5LTD';
    label vdif = 'assetvol - penultimate VA';
    label a = 'total firm value';
    label r1 = 'risk-free rate';
    label largev = 'one if assets, equity and f deflated';
    label mu = 'expected asset return';
run;

```

```

%mend itera;

%macro bob;
  %do i = &year_start. %to &year_end.;
    %do m = 1 %to 12;
      %itera(&i, &m);
    %end;
  %end;
%mend bob;

%bob;

```

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