EXAMINING THE EXISTENCE OF THE FINANCIAL DISTRESS RISK ANOMALY

EVIDENCE FROM THE U.S. STOCK MARKET

MAXIME RUNDSTRÖM

JOEL EJDESJÖ

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Abstract:

This paper examines the relationship between financial distress risk, estimated from a firm's distance-to-default, and equity returns on a sample of U.S. stocks between January 1990 and December 2019. We find monotonically decreasing returns in risk-sorted portfolios, while finding no risk-based explanation for these when benchmarking against the Fama-French three-factor and five-factor models. However, we do find that the Fama-French five-factor model appears to contribute with greater explanatory power. Additionally, we identify a financial distress risk anomaly yielding significant annualized monthly alphas in the range of 20-27% by constructing a long-short portfolio with a one-month holding period going long in the safest and short in the most distressed stocks. This effect is found to be stronger within a sub-sample of small stocks. Furthermore, the effect weakens as the holding period lengthens, with borderline significant and completely insignificant results for three-month and twelve-month holding periods respectively.

Keywords:

Financial distress risk anomaly, risk-sorted portfolios, Distance-to-Default, Fama-French five-factor model

Authors:

Maxime Rundström (24111)
Joel Ejdesjö (24218)

Tutors:

Marcus Opp, Associate Professor, Department of Finance

Examiner:

Adrien d'Avernas, Assistant Professor, Department of Finance

Bachelor Thesis
Bachelor Program in Business and Economics
Stockholm School of Economics

1. Introduction

One of the more puzzling asset pricing anomalies is the seemingly catastrophic performance of firms with high probability of default. The basic assumptions for asset pricing models and investment decisions derives from the concept that bearing higher idiosyncratic risk should deliver higher expected returns, while in the case of financial distress risk evidence has been presented that suggests this fundamental principle is violated. When sorting firms on distress risk, researchers have found that high probability of default forecast low returns (Dichev, 1998; Campbell et al., 2008; Garlappi et al. 2008; Gao et al., 2018). Since these firms tend to move together, this makes diversification difficult, which seems to imply that investors pay a premium for bearing financial distress risk. This has been coined the *financial distress anomaly*. Given the counter-intuitive nature of this relationship, these findings have attracted considerable interest from both academia and market practitioners. However, there seems to be no consensus in the applicable literature regarding the correct interpretation of the anomaly or even of its existence. For example, it has been proposed that lower than expected returns on distressed stocks in the U.S. during the 1980s may explain the anomaly (Chava and Purnandam, 2010).

Our paper contributes to this debate by examining if the results hold when considering a more recent sample and taking into account the Fama-French five-factor (2015) asset pricing model. While this model has remained largely untested by researchers when examining this anomaly, we believe that this extended model may provide additional explanatory power and shed some light on the reasons for poor performance of highly distressed stocks. Intuitively it makes sense to include the additional factors RMW and CMA, that are based on operating profitability and investment, as high performing firms with robust profitability and conservative levels of investment will likely have a lower risk of default, and vice versa.

We conduct an empirical analysis on a dataset of stocks listed on the major US stock exchanges (NYSE, AMEX and NASDAQ) between January 1990 and December 2019. We calculate a market-based proxy for financial distress risk following Vassalou and Xing (2004), the so-called distance-to-default measure. Each month we sort stocks into ten decile portfolios based on their probability of default. Following this, we make use of a long-short strategy of the safest and most distressed portfolios to characterize the financial distress risk anomaly. In doing this, we follow an approach similar to Campbell et al. (2008) and Gao et al. (2018). We risk-adjust our portfolio returns using the Fama-French three-factor model (1993), the Fama-French-Carhart four-factor that includes a momentum factor proposed by Carhart (1997), as well as the Fama-French five-factor model.

We find that our long-short strategy yields significant alphas for all included regression models when constructed on a one-month holding period. We obtain a CAPM alpha of 25.5%, Fama-French three-factor alpha of 26.9%, a Fama-French-Carhart four-factor alpha of 19.7% and finally a Fama-French five-factor alpha of 20.8%, all significant at $p<0.01$. Accordingly, we fail to find a risk-based explanation and our results thus indicate the presence of the financial distress risk anomaly within our sample. However, we do obtain significant negative factor loadings on RMW and CMA, which suggests that operating profitability and level of investment play an important role in determining the performance of distressed stocks. Thus, as a general rule, the magnitude of the alphas decreases when adjusting for the additional factors present in the Fama-French five factor model. Furthermore, we find evidence that the distress risk anomaly is more prevalent among smaller stocks and for shorter holding periods, while the relationship disappears when looking at a holding period of twelve months.

When risk-adjusting the portfolio returns we magnify the financial distress risk anomaly. The portfolio containing stocks with the highest financial distress risk delivers a significant negative annual average excess return of -13.2% and significant negative alphas in the range of -13.2% to -17.0%, while the portfolio containing stocks with the lowest financial distress risk delivers a significant positive annual average excess return of 5.4% and significant positive alphas in the range of 6.6% to 8.6% . Overall, we find that the average excess return over the market for the decile portfolios decline monotonically with increasing distress risk. This is similar to the findings of Griffin and Lemon (2002) and Campbell et al. (2008).

The remainder of the paper is organized as follows: In part two, we present the closest literature related to our topic and discuss the existing findings. We also consider the various measures available to proxy financial distress risk and explain how our research differs from other papers and our contribution to the literature. In part three, we discuss our data sources, our variable construction and our statistical analysis. In part four, we present the results of the empirical analysis performed. In part five, we conclude and discuss the implication of our findings, which includes a critical review of the limitations of our study and brief suggestions for directions on further research regarding this topic.

2. Literature review

Several studies have examined the returns of financially distressed stocks. Contrary to intuition, distressed equities are typically found to have extremely poor returns, a finding inconsistent with risk-based theory (Dichev, 1998 and Avramov et al., 2009). Furthermore, standard risk adjustments only seem to strengthen the effect (Griffin and Lemmon, 2002). This asset pricing irregularity has become known as the financial distress risk anomaly.

The literature is currently divided on the very existence of the anomaly as well as its correct interpretation. Vassalou and Xing (2004) find that distressed stocks are positively priced in the US stock market, while Campbell et al. (2008) form risk-sorted portfolios and argue that the returns of financially distressed stocks are in fact too low to be explained within a rational framework. Gao et al. (2018) also form risk-sorted decile portfolios but use a global dataset of 38 countries, finding the presence of a financial distress risk anomaly in developed markets in North America and Europe. This provide evidence against it being a US specific phenomenon. In contrast, Chava and Purnandam (2010) argue a positive relation between expected returns and distress risk, making the case that lower than expected returns on distressed stocks in the US in the 1980s explain the anomaly. That is, the anomaly may be an in-sample phenomenon that is unlikely to continue in the future.

Financial distress measures commonly used in research can be grouped into two separate categories; (1) accounting based measures such as Altman's (1968) Z-score and Ohlson's (1980) O-score and (2) market data based Distance-to-Default measure derived from the Black and Scholes (1973) and Merton (1974) option pricing models. Building upon Merton's model, Vassalou and Xing (2004) developed their own version of the Distance-to-Default as an alternative measure to predict bankruptcies. Gao et al. (2018) make use of Moody's proprietary KMV expected default frequencies, a market-based measure that is essentially a fine-tuning of the Distance-to-Default measure.

Fama and French (1996) make the case that their three-factor model can be used to explain some asset pricing anomalies relating to distressed stocks. The model has become the standard benchmark when examining the existence of the financial distress risk anomaly by many in the field, yet with limited explanatory power (Campbell et al., 2008 and Gao et al., 2018). This follows even with the addition of the momentum factor developed by Carhart (1997).

In this paper, our hope is to make progress on determining the existence of the financial distress risk anomaly by following a similar methodology as Campbell et al. (2008) and Gao et al. (2018). We follow the common approach of benchmarking against the Fama-French (1993) three-factor model and Fama-French-Carhart (1997) four-factor model but differentiate by also including the more recent Fama-French (2015) five-factor model. Largely untested in the financial distress risk anomaly literature, this newer model may offer some additional insights and help explain the poor stock returns. Additionally, we test the anomaly in a new setting, as we limit ourselves to the most recent thirty-year US sample in order to explore Chava and Purnandam's (2010) possible explanation for the observed stock returns. A common critique in the literature towards accounting based measures for estimating default risk is that accounting information is updated infrequently (Hillegeist et al., 2004). In addition, accounting models do not take into account the volatility of a firm's asset, which imply that firms with similar financial ratios will have similar likelihood of default (Vassalou and Xing, 2004). Therefore, we opt for a market-based measure. Due to restricted access to Moody's model, we choose to follow Vassalou and Xing's (2004) methodology and calculate the probability of default ourselves.

3. Data, variable construction and methodology

3.1 Raw data

We collect data on stock returns in the US from the monthly stock files of the Center for Research in Security Prices (CRSP). We limit our sample to the period January 1990 to December 2019. Corresponding accounting, financial and classification data is obtained from

Standard & Poor's Compustat North America – Daily. The variables are selected in order to be able to calculate value-weighted portfolio returns and Distance-to-Default (DD). Our initial sample contains approximately 4,000,000 monthly observations on stock returns and 2,200,000 monthly observations on accounting data. We also collect monthly data for the Fama-French three-factor model, five-factor model and the momentum factor from Kenneth R. French´s Data Library.

Given that leverage plays an important role in the Merton Model (1974), which is the basis for our calculation of the Distance-to-Default measure, we exclude all financial stocks. This is done by excluding all stocks with a Standard Industry Classification (SIC) Code between 6000-6999. Additionally, for the company each individual stock pertains to, we require that there is available data to calculate DD, or else the observation is omitted from the sample. This puts a lot of stress on data availability and leads to a limitation of our sample.

Following Gao et al. (2018), we apply a number of filters and conditions to minimize the influence of noise in our estimations. First, we limit our dataset to common stocks, those that are the primary securities of their respective company and those traded on the main US stock exchanges: New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and NASDAQ. Second, we require a stock to have at least 12 monthly returns in our sample period to be included. Third, in order to minimize the effects of bid-ask bounce we drop a particular stock-month observation if the month-end closing stock price is less than $5. We also drop all micro stocks, defined as stocks having a market cap below the 5^{th} percentile for that month.

Our final sample consist of 7,436 unique stocks and 782,316 stock-month observations. Table I provides a summary of the number of stocks by year. To get a better overview of how large our sample is we calculated the total market cap of the sample as a share of the total market cap of firms listed on the NYSE, AMEX and NASDAQ. A noticeable fact is the increase in the importance of our sample, based on market cap, over time. This is illustrated in Figure 1.

3.2 Measuring default risk

We follow Vassalou and Xing's (2004) market-based procedure to estimate the twelve-month distance-to-default measure, using Merton's (1974) model. In this model the equity of a firm is viewed as a call option on the firm's asset. The strike price of the call option is the book value of the firm's liabilities. Within this model, when the value of the firm's assets is less than the strike price, the value of equity is zero and the firm is assumed to default on its debt obligations.

The market value of equity, V_E is given by the (Black & Scholes, 1973) formula for call options:

$$V_E = V_A N(d_1) - X e^{-rT} N(d_2) \quad (1)$$

where

$$d_1 = \frac{\ln\left(\frac{V_A}{X}\right) + \left(r + \frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}}, \quad d_2 = d_1 - \sigma_A\sqrt{T} \tag{2}$$

where X_t is the book value of debt at time t that has maturity equal to T, r is the risk-free rate, and N is the normal cumulative distribution function. As a proxy for book value of debt we use the "current liabilities" plus half of "long-term debt" downloaded from the Compustat database. If "current liabilities" is unavailable, "long-term debt due in one year" is used instead. To calculate σ_A , we follow a similar procedure as in Vassalou and Xing (2004) and adopt an iterative process. We use monthly data from the past 12 months to obtain an estimate of the volatility of equity σ_E, which is then used as an initial value for the estimation of σ_A during the iterative process. Next, we make use of the Black-Scholes (1973) formula, and for each month of the past 12 months, we compute V_A using V_E as the market value of equity of that month. Thus, we are able to obtain monthly values for V_A . We then compute the standard deviation of those V_A, which is used 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. Our tolerance level for convergence is 10^{-4}. Most conversions require few iterations before reaching convergence (less than four). Once the converged value of σ_A is obtained, we use it to solve for V_A using equation (1).

The above process is then repeated at the end of every month, which results in estimated monthly values of σ_A. We keep the estimation window constant at 12 months for each iteration. The risk-free rate used for this process is the 1-year T-bill observed each month, obtained from the Federal Reserve Bank of St. Louis. Once monthly values of V_A are estimated, we can compute the mean of the change in $\ln(V_A)$, denoted as μ. Distance-to-default (DD) is then defined as follows:

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

If the ratio of value of assets to debt is less than 1 (i.e. its log becomes negative), then default occurs. Thus, the Distance-to-Default tells us by how many standard deviations the log of this ratio needs to differ from its mean for default to occur.

Using the normal distribution implied by Merton's model, the theoretical probability of default (PD) can be calculated for each firm each month using the following equation:

$$P_{def} = N(-DD) = N\left(-\frac{\ln\left(\frac{V_A}{X}\right) + \left(\mu - \frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}}\right) \tag{4}$$

This measure is used as a proxy for financial distress risk throughout our calculations. The aggregate probability of default (PD) is defined as the simple average of the P_{def} of all firms. Summary statistics for PD can be found in Table I. For the majority of the sample period, firms have an average 1-year probability of default around 1.5%. To give a better sense of how the probability of default evolve over time we provide a graph of PD for all stocks in our sample over the entire sample period. The shaded areas depict recession periods as defined by the NBER. The graph shows that default probabilities vary noticeably with the business cycle and surge during downturns, when credit-tightening occurs, such as during the financial crisis of 2007-2008. A more detailed mathematical derivation of equation (4) can be found in section one of the appendix.

3.3 Portfolio construction

We create portfolios following a similar procedure as Gao et al. (2018) and Campbell et al. (2008). At the end of each month t we rank all stocks in the sample based on their individual probability of default (Pdef). Based on this rank, we use percentile breakpoints to assign each stock to a certain portfolio, where the first decile consists of stocks with the lowest 10% Pdef-values and the tenth decile consists of the stocks with the highest 10% of Pdef-values. Denoting t the month of portfolio formation, we then calculate value-weighted returns for each portfolio over one month (t+2), three months (t+2 through t+4) and twelve months (t+2 through t+13). Using a holding period of one month as an example, if stock *X* is ranked in the first decile at the end of January, then *X* is used as component of the first decile portfolio starting at the end of February and held until the end of March at which point the portfolio is updated again based on the probability of default rankings at the end of February. Constructing the portfolios in this manner is done to reduce the effects of microstructure noise and extreme return reversal historically observed in the first month (t+1) as observed by Da and Gao (2010).

When calculating the returns of the portfolios with a holding period of three months and twelve months we make use of the overlapping portfolio approach outlined by Jeegadeesh and Titman (1993). Denoting K the holding period, then K overlapping portfolios are constructed. Stocks are held for K months each time the portfolio is updated based on new probability of default rankings, while also closing out the position initiated in month t-K. Thus, following this strategy the weights on 1/K of the securities in the portfolio are updated each month while the other weights are carried over from the previous month.

Following Campbell et al. (2008) we test the distress anomaly with a long-short trading strategy, forming a hedged portfolio long in stocks with the lowest 10% Pdef-values and short in stocks with the highest 10% Pdef-values. This strategy would effectively take advantage of the financial distress risk anomaly if it exists. We do this for our entire stock sample, and then report results for two additional size groups: large stocks and small stocks, with the NYSE median market capitalization used as a cutoff value between the two.

Table I.
Number of stocks and summary statistics for the default measure

This table lists the total number of unique stocks in our final sample by year, share of total market capitalization, average twelve-month probability of default (PD) by year, as well as the median, standard deviation, minimum and maximum PD by year. Probability of default is estimated using Distance-to-Default, following Vassalou and Xing (2004). Share of total market capitalization is computed as the total market capitalization of firms in our sample divided by the total market capitalization of firms listed on the NYSE, AMEX and NASDAQ stock exchanges (excluding financial firms with SIC codes between 6000-6999 in both cases).

Year	Number of stocks	Share of total market cap	Average PD	Median PD	Std. dev. PD	Min PD	Max PD
1990	1448	71%	0.031	0.027	0.006	0.025	0.042
1991	1521	72%	0.007	0.007	0.001	0.006	0.009
1992	1723	72%	0.009	0.009	0.001	0.008	0.011
1993	1932	69%	0.007	0.007	0.001	0.005	0.009
1994	2117	70%	0.010	0.010	0.002	0.007	0.013
1995	2277	70%	0.006	0.007	0.001	0.005	0.008
1996	2502	70%	0.007	0.008	0.001	0.005	0.009
1997	2587	72%	0.007	0.007	0.001	0.006	0.010
1998	2577	73%	0.022	0.019	0.008	0.014	0.032
1999	2581	73%	0.022	0.020	0.005	0.015	0.030
2000	2612	72%	0.046	0.047	0.008	0.032	0.057
2001	2339	79%	0.023	0.022	0.002	0.019	0.026
2002	2172	82%	0.030	0.029	0.003	0.026	0.035
2003	2231	81%	0.004	0.004	0.000	0.003	0.005
2004	2343	80%	0.005	0.005	0.001	0.004	0.006
2005	2369	82%	0.007	0.007	0.001	0.006	0.009
2006	2458	83%	0.003	0.004	0.000	0.003	0.004
2007	2506	84%	0.010	0.009	0.004	0.006	0.018
2008	2278	87%	0.071	0.065	0.021	0.050	0.109
2009	2054	86%	0.008	0.008	0.002	0.005	0.013
2010	2249	86%	0.005	0.004	0.001	0.004	0.006
2011	2321	88%	0.013	0.011	0.004	0.008	0.020
2012	2269	88%	0.005	0.005	0.001	0.004	0.006
2013	2376	91%	0.004	0.004	0.000	0.003	0.005
2014	2531	92%	0.007	0.007	0.002	0.005	0.011
2015	2598	93%	0.018	0.015	0.006	0.012	0.027
2016	2560	94%	0.011	0.011	0.001	0.009	0.012
2017	2601	94%	0.009	0.009	0.001	0.007	0.011
2018	2679	94%	0.020	0.017	0.005	0.014	0.031
2019	2872	96%	0.013	0.013	0.001	0.011	0.015

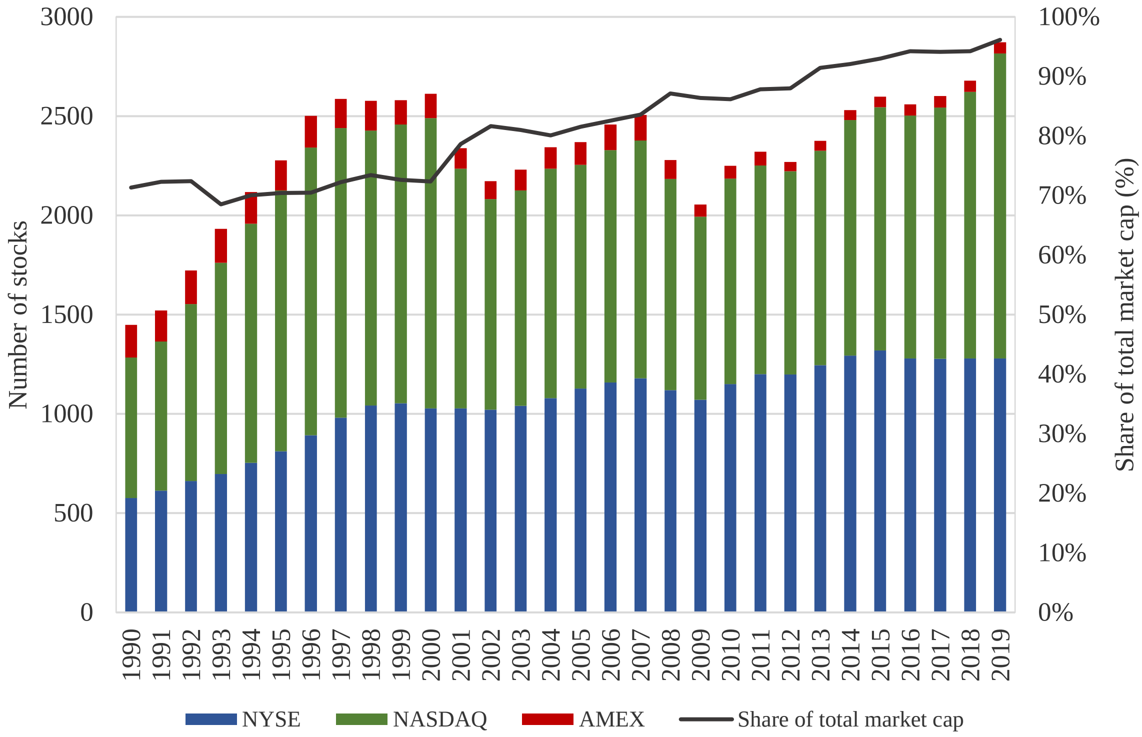

Figure 1. Number of stocks per year

We plot the total number of stocks in our sample per year and by stock exchange (left). On the secondary axis (right) the market capitalization of our final stock sample is plotted as a share of the total market capitalization of stocks listed on the NYSE, NASDAQ and AMEX.

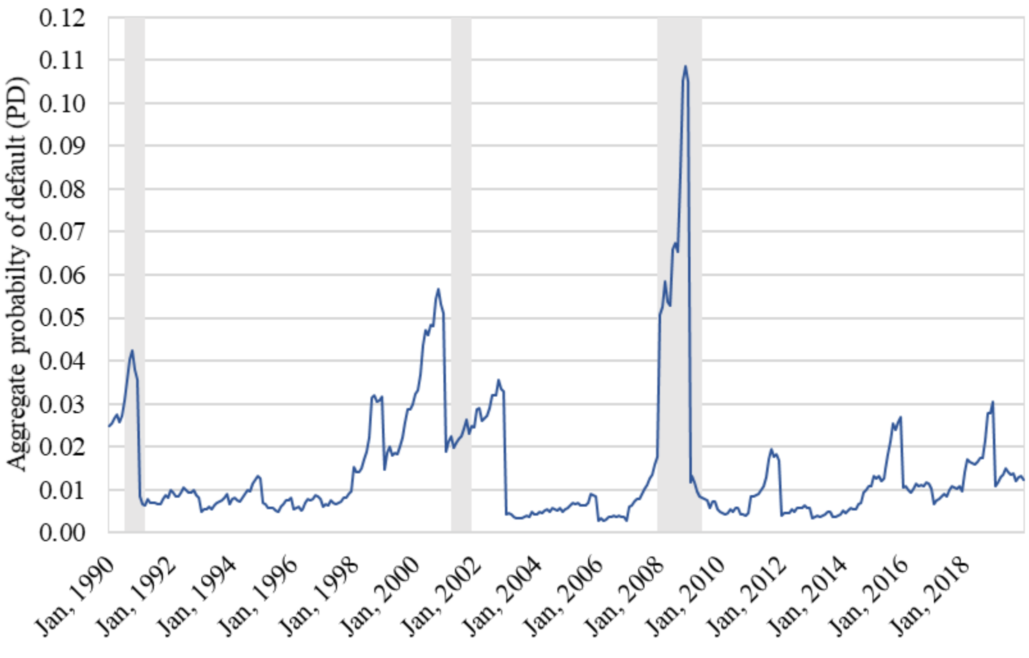

Figure 2. Aggregate probability of default

Probability of default is estimated using Distance-to-Default, following Vassalou and Xing (2004). The aggregate PD is defined as the simple average of the Pdef of all firms, calculated for each month. The shaded areas depict recession periods, as defined by NBER.

3.4 Statistical Analysis

To evaluate the distress anomaly, we acknowledge that stocks differing in distress risk may also differ in their exposure to traditional risk factors. Following the previous literature, we believe the market risk in CAPM (Beta) and the additional factors, book-to-market and size in the Fama-French three-factor model may explain some of the risk. To take any eventual momentum effect into account we also include the extended four-factor model proposed by Carhart (1997). Furthermore, we evaluate the exposure to the new factors proposed in the Fama-French five-factor model: the operating profitability and investment factors. We use ordinary least-squares (OLS) regressions to estimate the alpha of each individual portfolio.

Our specifications for running the linear regressions are the following:

$$R_{it} - rf_t = a_i + b_1(R_{Mt} - rf_t) + e_{it} \tag{5}$$

$$R_{it} - rf_t = a_i + b_1(R_{Mt} - rf_t) + b_2 SMB_t + b_3 HML_t + e_{it} \tag{6}$$

$$R_{it} - rf_t = a_i + b_1(R_{Mt} - rf_t) + b_2 SMB_t + b_3 HML_t + b_4 UMD_t + e_{it} \tag{7}$$

$$R_{it} - rf_t = a_i + b_1(R_{Mt} - rf_t) + b_2 SMB_t + b_3 HML_t + b_4 RMW_t + b_5 CMA_t + e_{it} \tag{8}$$

where equation (5) is the CAPM-model, (6) is the Fama-French three-factor model, (7) is the Fama-French-Carhart four-factor model and (8) is the Fama-French five-factor model. $R_{it} - rf_t$ represents portfolio i´s return in excess of the 1-month US Treasury bill rate; R_{Mt} is the market return; SMB_t is the factor mimicking portfolio for returns on small minus big stocks; HML_t the factor mimicking portfolio for returns on high minus low book-to-market equity (BE/ME); UMD_t is the factor mimicking portfolio for returns on high prior returns (Up) minus low prior returns (Down); RMW_t is the factor mimicking portfolio for returns on robust minus weak operating profitability and CMA_t is the factor mimicking returns on the conservative minus aggressive investment portfolios.

We calculate sample-specific Fama-French factors by following the methodology outlined in Fama and French (1993, 2015). Details on our factor construction can be found in Appendix 2. Summary statistics for the sample-specific factors and the ones obtained from Kenneth R. French's Data Library are presented in Table II. Interestingly, our sample seem to slightly differ from the market as whole, as the sample-specific SMB and RMW factors average negative returns. Following this discovery, we opt to run our regressions against the factors directly obtained from the Kenneth R. French's Data Library.

Table II.
A comparison of market and sample-specific Fama-French factors

This table presents mean, median, standard deviation, minimum and maximum (in percentage units) for the sample-specific Fama-French factors calculated based on our final stock sample. For the purpose of comparison we also include the factors obtained from the Kenneth R. French's Data Library. The (S) denotes the sample-specific factors.

Factor	Mean	Median	Std. dev.	Min	Max
RMRF	0.669	1.185	4.234	-17.230	11.350
RMRF (S)	0.724	1.134	4.204	-16.716	11.006
SMB	0.133	0.085	3.017	-14.910	18.320
SMB (S)	-0.172	-0.330	3.367	-21.317	15.782
HML	0.139	-0.105	2.976	-11.180	12.870
HML (S)	0.026	0.072	2.090	-9.216	6.277
RMW	0.345	0.385	2.571	-18.340	13.330
RMW (S)	-0.215	0.107	3.173	-18.584	18.099
CMA	0.193	-0.020	2.056	-6.860	9.560
CMA (S)	0.156	-0.003	3.783	-18.870	21.420

4. Empirical Analysis

Our empirical analysis proceeds in two steps. First, we look at the returns of the distress risk-sorted portfolios and their loadings on the Fama-French factors when running the regressions. Second, we examine the returns of the long-short portfolios used to characterize the financial distress risk anomaly, examining how size as well as longer holding periods impact the portfolio returns.

4.1 Returns on distress risk-sorted stock portfolios

Table III reports the result for our ten risk-sorted decile portfolios. Each portfolio is denoted by the percentile breakpoints of their probability of default (Pdef) ranking used to construct it, for example portfolio 0010 is the 0^{th} to 10^{th} percentile percentile of stocks (lowest risk of default) and portfolio 9000 is formed based on the 90^{th} to 100^{th} percentile of stocks (highest risk of default). Panel A reports average annualized monthly simple excess returns over the market and annualized monthly alphas with respect to the CAPM, the three- and five-factor model of Fama and French (1993, 2015) and the Fama-French-Carhart four-factor model (Carhart 1997). Panel B shows the coefficients of the Fama-French three-factor model regressions and Panel C shows the coefficients of the five-factor model regressions. The *t*-statistics are included below in parentheses. Panel D shows a selection of portfolio characteristics. These include annualized standard deviation of individual and portfolio returns, mean RSIZE (computed as the log of mean firm market capitalization divided by the total market value of the S&P 500), average market-to-book ratio (MB), average operating profitability (computed as the total revenue minus cost of goods sold, selling, general and administrative expense and interest and related expense divided by book equity), average investment ratio (computed as the change in total assets) and the average probability of default.

Table III
Returns on distress risk-sorted stock portfolios

At the end of month t, we sort all stocks in our sample into ten portfolios based on their 12-month probability of default. For example, portfolio 0010 corresponds to the 0^{th} to 10^{th} percentile of stocks and portfolio 1020 corresponds the 10^{th} to 20^{th} percentile of stocks. Our portfolio strategy involves buying the stocks one month after portfolio formation, i.e. at the beginning of month t+2. The table shows results from regressions of value-weighted excess return over the market, as well as three ((RMRF, HML, SMB), four (RMRF, HML, SMB, UMD) and five ((RMRF, HML, SMB, RMW, CMA) Fama-French factor regressions. The sample period is January-1990 to December-2019. Panel A shows the annualized mean excess return as well as monthly annualized alphas from these regressions and the resulting absolute value of t-statistics (in parenthesis). Panel B shows the loadings on the three factors and the resulting absolute value of t-statistics (in parenthesis) from the three-factor regression. Panel C shows the loading on the five factors and the resulting absolute value of t-statistics (in parenthesis) from the five-factor regression. Panel D reports standard deviation of individual and portfolio returns, mean relative size (RSIZE) defined as the log of the mean market cap divided by the total market value of the S&P500, mean market-to-book ratio (MB), mean operating profitability (OP) defined as total revenue minus cost of goods sold, selling, general and administrative expense and interest and related expense divided by book equity, the mean investment ratio (INV) calculated as the change in total assets each year and average probability of default (Pdef) values for each portfolio. * denotes significant at 5%, ** denotes significant at 1%.

Portfolios	0010	1020	2030	3040	4050	5060	6070	7080	8090	9000
Panel A. Portfolio Alphas										
Mean excess return	5.35%	3.78%	3.81%	-0.25%	-1.05%	-3.56%	-4.97%	-7.34%	-11.93%	-13.18%
	(3.70)**	(3.32)**	(3.23)**	(0.23)	(0.77)	(2.47)*	(3.09)**	(3.69)**	(5.40)**	(4.91)**
CAPM alpha	8.15%	5.74%	4.65%	0.05%	-1.32%	-4.45%	-6.51%	-9.93%	-14.98%	-16.35%
	(7.02)**	(5.94)**	(3.98)**	(0.04)	(0.96)	(3.12)**	(4.26)**	(5.60)**	(7.82)**	(6.77)**
3-factor alpha	8.61%	6.07%	5.04%	0.13%	-1.22%	-4.51%	-6.85%	-10.10%	-15.49%	-16.98%
	(7.92)**	(6.64)**	(4.45)**	(0.12)	(0.90)	(3.23)**	(4.63)**	(6.07)**	(8.47)**	(7.44)**
4-factor alpha	6.89%	5.30%	4.89%	-0.15%	-1.24%	-3.86%	-5.56%	-8.15%	-13.27%	-13.21%
	(7.10)**	(5.92)**	(4.24)**	(0.13)	(0.90)	(2.74)**	(3.82)**	(5.14)**	(7.68)**	(6.63)**
5-factor alpha	6.60%	5.20%	4.64%	-0.46%	-2.51%	-5.28%	-6.74%	-9.21%	-14.46%	-14.26%
	(6.18)**	(5.55)**	(3.94)**	(0.40)	(1.82)	(3.66)**	(4.36)**	(5.29)**	(7.58)**	(6.04)**
Panel B. Three-Factor Regression Coefficients										
RMRF	0.682	0.777	0.900	0.962	1.012	1.090	1.184	1.301	1.411	1.421
	(32.50)**	(43.53)**	(40.43)**	(43.18)**	(36.93)**	(38.02)**	(38.61)**	(37.10)**	(35.64)**	(28.54)**
SMB	-0.175	-0.143	-0.104	-0.015	0.107	0.163	0.197	0.345	0.288	0.415
	(6.09)**	(5.85)**	(3.40)**	(0.49)	(2.85)**	(4.15)**	(4.69)**	(7.18)**	(5.31)**	(6.08)**
HML	-0.170	-0.125	-0.149	-0.032	-0.033	0.033	0.146	0.087	0.237	0.300
	(5.65)**	(4.90)**	(4.66)**	(1.01)	(0.85)	(0.80)	(3.32)**	(1.74)	(4.19)**	(4.21)**
Panel C. Five-Factor Regression Coefficients										
RMRF	0.753	0.805	0.913	0.980	1.068	1.112	1.179	1.264	1.363	1.296
	(32.59)**	(39.45)**	(35.58)**	(38.14)**	(34.43)**	(33.79)**	(33.17)**	(31.19)**	(29.89)**	(22.98)**
SMB	-0.114	-0.105	-0.090	0.021	0.131	0.222	0.200	0.309	0.262	0.322
	(3.71)**	(3.87)**	(2.64)**	(0.61)	(3.18)**	(5.08)**	(4.24)**	(5.75)**	(4.34)**	(4.30)**
HML	-0.285	-0.147	-0.144	-0.056	-0.203	-0.023	0.116	0.094	0.284	0.500
	(7.23)**	(4.24)**	(3.29)**	(1.27)	(3.84)**	(0.41)	(1.92)	(1.36)	(3.66)**	(5.20)**
RMW	0.231	0.126	0.075	0.100	0.088	0.149	-0.021	-0.136	-0.142	-0.356
	(5.64)**	(3.48)**	(1.65)	(2.20)*	(1.60)	(2.56)*	(0.34)	(1.89)	(1.76)	(3.56)**
CMA	0.213	0.041	-0.011	0.006	0.306	-0.016	0.002	-0.080	-0.146	-0.439
	(3.69)**	(0.80)	(0.17)	(0.10)	(3.95)**	(0.20)	(0.03)	(0.79)	(1.28)	(3.12)**
Panel D. Portfolio Characteristics										
Portfolio SD	0.116	0.123	0.146	0.153	0.169	0.181	0.196	0.222	0.237	0.256
Individual SD	0.306	0.327	0.362	0.382	0.405	0.431	0.462	0.495	0.543	0.656
Mean RSIZE	-8.706	-8.716	-8.801	-9.011	-9.212	-9.393	-9.526	-9.708	-9.874	-10.095
Mean MB	4.310	4.232	3.867	3.694	3.128	3.346	3.036	2.526	2.272	2.134
Mean OP	0.332	0.345	0.324	0.273	0.310	0.285	0.303	0.277	0.278	0.261
Mean INV	0.140	0.144	0.167	0.170	0.183	0.184	0.189	0.221	0.260	0.252
Mean PD	0.019%	0.014%	0.034%	0.052%	0.080%	0.114%	0.229%	0.534%	1.523%	11.577%

The average annual excess returns reported in the first row of Table III decline monotonically with increasing financial distress risk. The most distressed portfolio delivers a significant negative annual average excess returns of -13.2% and the safest portfolio a significant positive annual average excess return of 5.4%, which constitutes a difference of 18.6 percentage points. Similarly, portfolio standard deviation increases monotonically with increasing financial distress risk. This results in progressively lower Sharpe ratios for the portfolios with higher probability of default (Pdef) for each portfolio. As a form of robustness check, we also present results of regressions against our sample-specific factors in Appendix 3.

When correcting for risk, all portfolios up to the 30^{th} percentile boast significant positive alphas and all portfolios beyond the 50^{th} percentile have significant negative alphas when regressing against the four asset pricing models. When risk-adjusting the portfolio returns using the CAPM and Fama-French three-factor the contrast in portfolio performance increases, magnifying the pattern observed with the average excess return. This is a similar finding as to what Griffin and Lemon (2002) and Campbell et al. (2008) observed. When risk-adjusting using the Fama-French five-factor model the observed magnitude of the alphas decrease for the three least and three most distressed portfolios. As expected, this model contributes with greater explanatory power. Nevertheless, the alphas continue to be greater than the average mean excess return. Similar results for alpha are found when regressing against the Fama-French-Carhart four-factors. As an example, portfolio 9000 has an average excess return of -13.2% with a t-statistic of 4.9; a CAPM alpha of -16.4% with a t-statistic of 6.8; a Fama-French three-factor alpha of -17.0% with a t-statistic of 7.4; a Fama-French-Carhart four-factor alpha of -13.2% with a t-statistic of 6.6; and a Fama-French five-factor alpha of -14.3% with a t-statistic of 6.0. The average excess return and alphas of each portfolio are illustrated in Figure 3.

Several trends among the factor coefficients of each portfolio found in Panel C of Table III can be identified. For the Fama-French five-factor regressions the loadings on RMRF increase with higher default probabilities. Similar results are obtained for SMB, which is illustrated in Figure 4. This is expected as distressed stocks are much smaller than safe stocks, as can be seen in Panel D of Table III. The value-weighted average size of the 10% least distressed stocks is over four times larger than the value-weighted average size of the 10% most distressed stocks. The loadings on HML for each portfolio also increase when looking at higher default probabilities. Again, this can be expected as the more distressed stocks have a lower average market-to-book ratio, as seen in Panel D of Table III. Thus, they contain a prevalence of value stocks. This is in contrast to the findings of Campbell et al. (2008) who find that market-to-book ratios are high for decile portfolios with the safest stocks and for the portfolios with the most distressed stocks, while still having high loadings on HML.

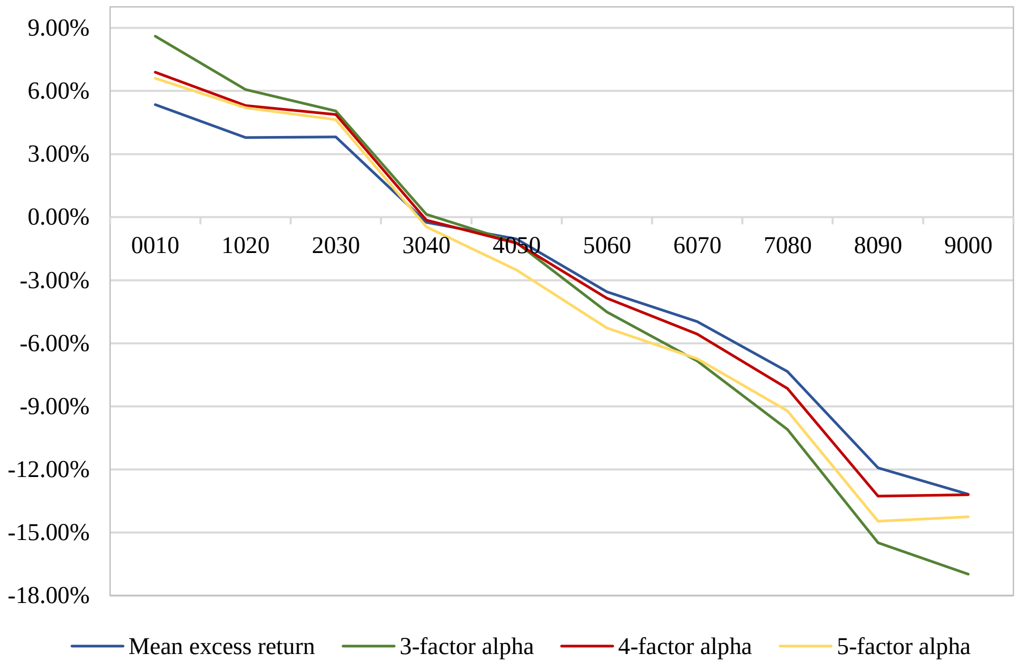

Figure 3. Alphas of distressed stock portfolios. Risk-sorted decile portfolios are formed at the beginning of every month using the 12-month probability of default (Pdef). The figure plots the annualized monthly mean excess return over the market for the 10 distress risk-sorted decile portfolios from January-1990 to December-2019, as well as the annualized monthly alphas resulting from CAPM, Fama-French three-factor, Fama-French-Carhart four-factor, and Fama-French five-factor regressions.

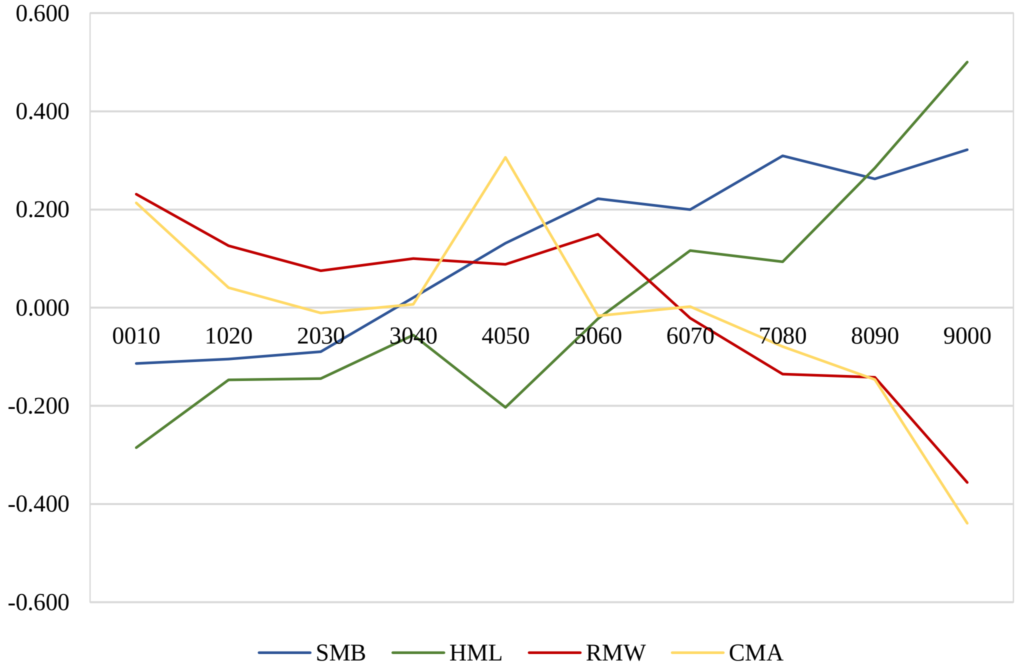

Figure 4. Factor loadings of distressed stock portfolios (five-factor regression). Risk-sorted decile portfolios are formed at the beginning of every month using the 12-month probability of default (Pdef).The figure plots loadings on the value factor (HML), the size factor (SMB), the profitability factor (RMW) and the investment factor (CMA) following a Fama-French five-factor regression on the portfolio returns over our entire sample period (January-1990 to December-2019).

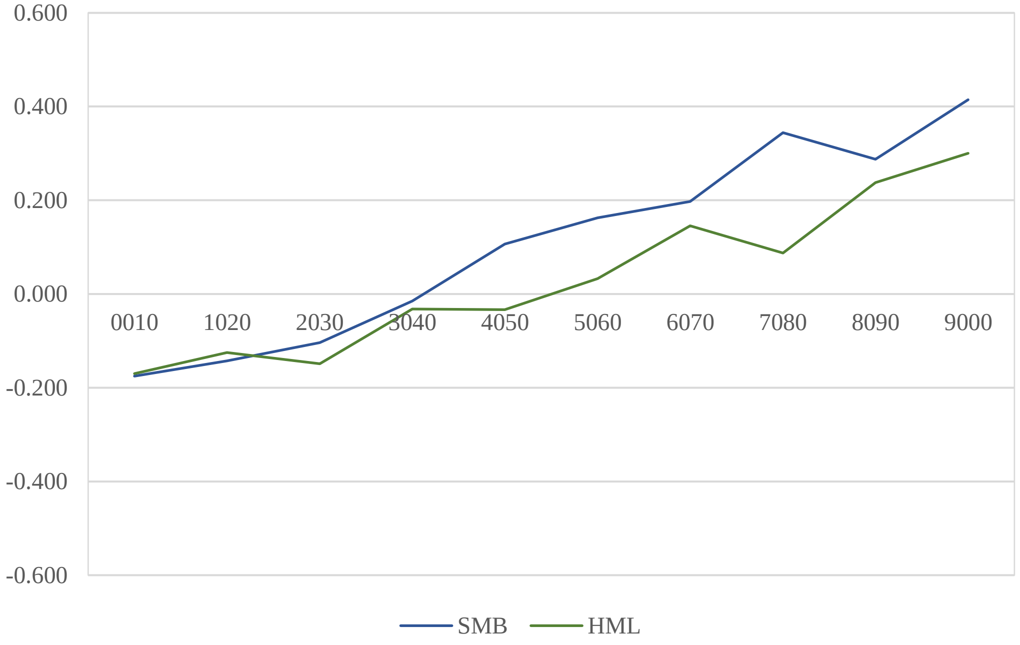

Figure 5. Factor loadings of distressed stock portfolios (three-factor regression). Risk-sorted decile portfolios are formed at the beginning of every month using the 12-month probability of default (Pdef).This figure plots loadings on the value factor (HML) and the size factor (SMB) following a Fama-French three-factor regression on the portfolio returns over our entire sample period (January-1990 to December-2019).

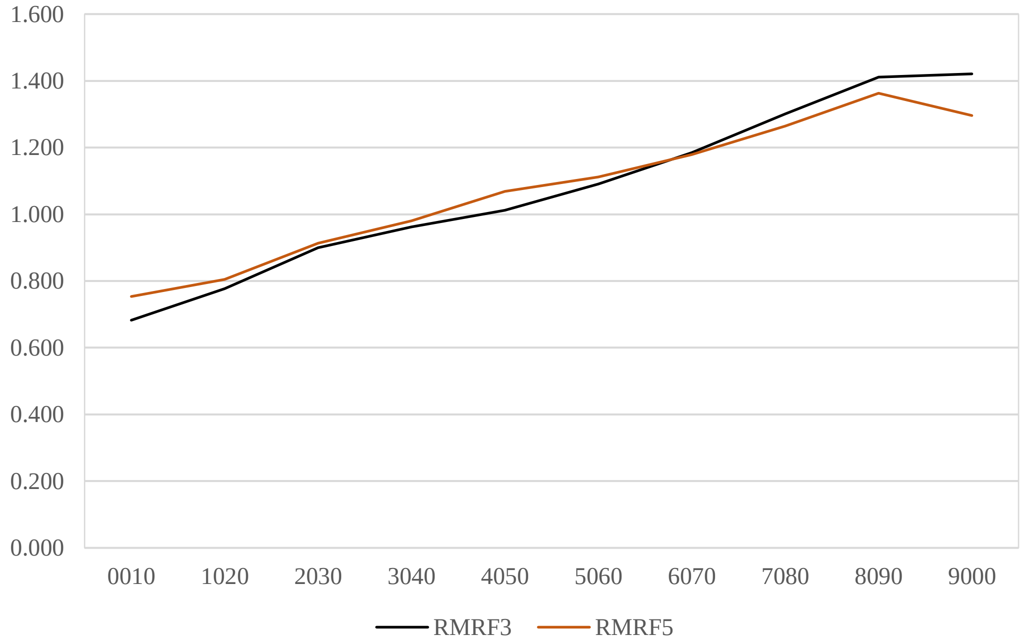

Figure 6. RMRF loadings of distressed stock portfolios. Risk-sorted decile portfolios are formed at the beginning of every month using the 12-month probability of default (Pdef).This figure plots loadings on the market return factor (RMRF) for both a Fama-French three-factor and Fama-French five-factor regression on the portfolio returns over our entire sample period (January-1990 to December-2019).

The coefficients of the profitability (RMW) and investment (CMA) factors show a striking opposite behavior. The loadings for these are increasingly negative with higher distress risk, as illustrated in Figure 4. For portfolio 0010 (safest) and portfolio 9000 (highest risk of default) we obtain positive and negative loadings respectively at a significance level of $p<0.01$. These loadings are in line with their respective portfolio characteristics, as the stocks in portfolio 0010 have an average profitability of 33.2% and a rather conservative investment ratio of 14.0%, compared to 26.1% and 25.2% for portfolio 9000. Rather expectedly, this suggest that poor operating profitability and aggressive investing explains some of the poor returns for distressed stocks.

To facilitate comparisons with prior studies we include the factor loadings for the three-factor regression in Panel B as well as an illustration of those in Figure 5, as well as a graph of the loadings on the market factor (RMRF) for both the three-factor and five-factor regressions, as seen in Figure 6. The pattern of higher loadings on the RMRF, SMB and HML factors for the distressed stocks can also be observed here. These results are pessimistic for the view that higher distress risk is positively priced, as distressed stocks have lower average returns despite their significant high loadings on RMRF, SMB and HML factors.

4.2 Returns on hedged long-short portfolios

Table IV reports the results for our hedged long-short portfolios, going long in the top 10% safest stocks and short in the 10% of stocks with highest probability of default. Portfolio returns are calculated for all stocks in our sample and two other size groups: large stocks and small stocks. Results are presented for one-month (t+2), three-month (t+2 through t+4) and twelve-month (t+2 through t+13) holding periods, where t denotes the month for portfolio formation. Similar to Table III, Panel A reports average annualized monthly simple excess returns over the market and annualized monthly alphas with respect to the CAPM, the three- and five-factor model of Fama and French (1993, 2015) and the Fama-French-Carhart four-factor model (Carhart 1997). Panel B shows the coefficients of the Fama-French three-factor model regressions and Panel C shows the coefficients of the five-factor model regressions. These are included for the sake of transparency in order to be comparable with prior studies. The *t*-statistics are included below in parentheses.

The returns on the portfolio with a one month holding period suggests that there is indeed a financial distress risk anomaly. We observe significant alphas for all regression models, with a Fama-French three-factor alpha of 26.9% (t=7.8) and a slightly lower Fama-French five-factor alpha of 20.8% (t=6.2) for the all stocks sample. Similar to what was observed when looking at the individual decile portfolios, the alphas decrease when adding the explanatory power of the RMW and CMA factors. The second column shows the same results but for large firms, with a Fama-French three-factor alpha of 24.9% (t=8.2) and a Fama-French five-factor alpha of 20.0% (t=6.6). The alphas for the small firm portfolio are the largest, with a 33.9% (t=12.6) Fama-French three-factor alpha and a 29.3% (t=12.2) Fama-French five-factor alpha. Although this one-month holding period portfolio vastly outperforms the market in all three size groups, the small firm portfolio average excess return of 16.4% (t=3.0) is the only one that is significant.

Table IV
Returns on hedged long-short portfolios

At the end of month t, we sort stocks into ten portfolios based on their 12-month probability of default. This is done for all stocks in our sample as well as two sub-samples; large stocks and small stocks, where the market capitalization cutoff value for large versus small stocks is the NYSE median market capitalization. The hedged long-short portfolio strategy consists of buying the stocks in the top decile with lowest probability of default and short-selling the stocks in the decile with highest probability of default, beginning one month after portfolio formation, i.e. at the beginning of month t+2. Value-weighted portfolio returns are calculated for one-month, three-month and twelve-month holding periods using an overlapping portfolio method. The sample period is January-1990 to December-2019. The table shows results from regressions of value-weighted excess return over the market, as well as three (RMRF, HML, SMB), four (RMRF, HML, SMB, UMD) and five (RMRF, HML, SMB, RMW, CMA) Fama-French factor regressions. Panel A shows the annualized mean excess return as well as monthly annualized alphas from these regressions and the resulting absolute value of t-statistics (in parenthesis). Panel B shows the loadings on the three factors and the resulting absolute value of t-statistics (in parenthesis) from the three-factor regression. Panel C shows the loading on the five factors and the resulting absolute value of t-statistics (in parenthesis) from the five-factor regression. * denotes significant at 5%, ** denotes significant at 1%.

Holding periods		t+2			t+2, t+4			t+2, t+13	
Sample	all	large	small	all	large	small	all	large	small
Panel A. Portfolio Alphas									
Mean excess return	8.90%	7.17%	16.41%	-4.90%	-5.93%	-0.56%	-10.73%	-8.94%	-12.57%
	(1.48)	(1.24)	(2.96)**	(0.79)	(1.02)	(0.09)	(2.51)*	(2.15)*	(4.44)**
CAPM alpha	25.45%	23.53%	33.05%	10.39%	8.96%	15.07%	-0.28%	1.78%	-4.93%
	(6.91)**	(7.38)**	(11.56)**	(2.47)*	(2.52)*	(3.52)**	(0.10)	(0.77)	(4.22)**
3-factor alpha	26.89%	24.90%	33.88%	12.20%	10.50%	17.17%	1.21%	3.02%	-4.77%
	(7.84)**	(8.18)**	(12.55)**	(3.14)**	(3.11)**	(5.15)**	(0.53)	(1.42)	(4.10)**
4-factor alpha	19.70%	18.81%	29.30%	3.88%	3.60%	10.06%	-2.47%	-0.73%	-5.35%
	(7.19)**	(7.54)**	(12.23)**	(1.32)	(1.37)	(3.91)**	(1.23)	(0.41)	(4.60)**
5-factor alpha	20.76%	20.03%	30.69%	6.61%	5.26%	13.87%	0.15%	1.70%	-4.98%
	(6.18)**	(6.64)**	(11.22)**	(1.72)	(1.59)	(4.12)**	(0.06)	(0.78)	(4.13)**
Panel B. Three-Factor Regression Coefficients									
RMRF	-0.737	-0.782	-0.650	-0.813	-0.823	-0.696	-0.351	-0.381	-0.029
	(11.97)**	(14.20)**	(13.76)**	(10.97)**	(12.73)**	(11.20)**	(7.64)**	(9.07)**	(1.22)
SMB	-0.586	-0.341	-0.430	-0.717	-0.423	-1.269	-0.511	-0.325	-0.082
	(6.94)**	(4.52)**	(6.65)**	(7.06)**	(4.78)**	(14.91)**	(8.12)**	(5.66)**	(2.51)*
HML	-0.471	-0.448	-0.263	-0.660	-0.561	-0.752	-0.589	-0.479	-0.070
	(5.34)**	(5.68)**	(3.89)**	(6.22)**	(6.06)**	(8.46)**	(8.95)**	(7.98)**	(2.06)*
Panel C. Five-Factor Regression Coefficients									
RMRF	-0.541	-0.621	-0.569	-0.623	-0.650	-0.590	-0.311	-0.331	-0.029
	(7.90)**	(10.08)**	(10.58)**	(7.48)**	(9.02)**	(8.36)**	(5.88)**	(6.86)**	(1.05)
SMB	-0.432	-0.233	-0.303	-0.526	-0.218	-1.165	-0.483	-0.294	-0.045
	(4.75)**	(2.84)**	(4.25)**	(4.76)**	(2.28)*	(12.46)**	(6.89)**	(4.59)**	(1.24)
HML	-0.787	-0.742	-0.317	-0.900	-0.807	-0.695	-0.559	-0.510	-0.032
	(6.73)**	(7.06)**	(3.46)**	(6.34)**	(6.56)**	(5.79)**	(6.20)**	(6.21)**	(0.67)
RMW	0.585	0.443	0.397	0.690	0.694	0.452	0.170	0.182	0.088
	(4.81)**	(4.05)**	(4.17)**	(4.67)**	(5.43)**	(3.62)**	(1.81)	(2.13)*	(1.80)
CMA	0.653	0.582	0.082	0.472	0.364	0.127	0.039	0.100	-0.105
	(3.81)**	(3.78)**	(0.61)	(2.27)*	(2.02)*	(0.72)	(0.29)	(0.83)	(1.53)

Moving across Table IV, the results weaken as the holding period increases. Over a holding period of three months the average excess return is negative, although non-significant. Significant Fama-French three-factor alphas can still be observed for all three size groups, at 12.2% (t=3.1), 10.5% (t=3.1) and 17.2% (t=5.2) for all firms, large firms and small firms respectively. However, when regressing against the Fama-French-Carhart four-factor or the Fama-French five-factor models, the alphas become insignificant for the sample of all firms as well as the sample of large firms. This hints at the limitations of the Fama-French three-factor model when it comes to distressed stocks, as one may incorrectly characterize some findings as being evidence for the financial distress risk anomaly. Continuing to the right, the small firms sample continue to boast significant alphas, with a Fama-French-Carhart four-factor alpha of 10.1% (t=3.9) and Fama-French five-factor alpha of 13.9% (t=4.1). This highlights the stronger presence of the financial distress risk anomaly among smaller firms, as hinted at by the factor loadings discussed in the prior section.

At a twelve-month holding period, the general trend breaks down. Results for the sample of all firms and the sample of large firms are insignificant, while the returns for the small firm portfolio now produces significant negative alphas, such as a Fama-French five-factor alpha of -5.0% (t=4.1). This suggests that the financial distress anomaly weakens at longer time horizons until it breaks down completely.

Gao et al. (2018) find alphas of around 5-6% when examining a relatively new sample over a shorter time period (between January 1992 and June 2013), hypothesizing that increased awareness has alleviated mispricing by rational arbitrageurs. Our findings are discouraging for this view, as the magnitude of our alphas are similar to other prior studies studying U.S. firms, such as Campbell et al. (2008) whom reports significant Fama-French three-factor alphas in the range of 20-25%.

Figure 7 illustrates the performance of the long-short portfolio over time. For the sake of comparison, the cumulative return of the S&P500 is also plotted. The performance of the portfolio is measured in two ways: 1) by cumulative risk-adjusted return from the Fama-French five-factor model and by 2) cumulative excess return over the market. As can be observed in the graph, the alphas of the portfolio are much more consistent over time, while the raw returns experience several longer periods of decline. Furthermore, to clearly illustrate the relationship between the monthly portfolio returns and the aggregate probability of default (PD), these are laid out over each other in Figure 8.

Figure 7. Cumulative returns on the hedged long-short distressed stock portfolio. Risk-sorted decile portfolios are formed at the beginning of every month using the 12-month probability of default (Pdef). The figure plots cumulative excess returns over the market as well as the cumulative returns of Fama-French five-factor alphas for the long-short portfolio going long in the safest decile and short in the riskiest decile, with a one-month holding period before rebalancing, constructed from all firms in our sample. The cumulative market return (S&P 500) for our sample period January-1990 to December-2019 is also included.

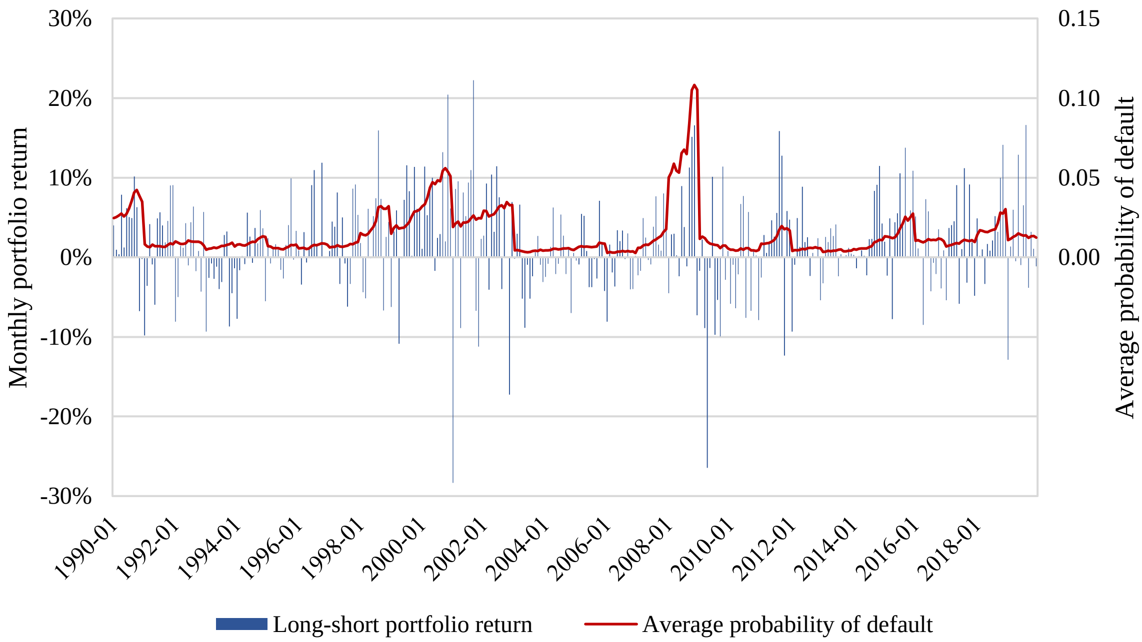

Figure 8. Monthly returns of the hedged long-short distressed stock portfolio. Risk-sorted decile portfolios are formed at the beginning of every month using the 12-month probability of default (Pdef). A long-short portfolio is formed, going long in the safest decile and short in the riskiest decile, with a one-month holding period before rebalancing, constructed from all firms in our sample. The figure plots the annualized monthly portfolio return with a one-month holding period (left) and the average 12-month probability of default (right) for all stocks in our sample.

5. Conclusion

We characterize the financial distress risk anomaly with a long-short trading strategy and find a negative relation between distress risk and stock returns in the U.S. stock market over our sample period (January 1990 – December 2019). Stocks with a higher probability of default delivers anomalously lower average return, underperforming the market at a significant level. We obtain significant negative alphas when risk-adjusting returns for the three-, four- and five-factor models. In fact, these standard risk-adjustment practices only magnify the difference in performance between low and high-risk stocks. Our findings provide further evidence to the view that the financial distress risk anomaly does likely exist in U.S. stock markets. When examining different size groups and holding periods the distress risk anomaly appears to be stronger among small stocks and for shorter holding periods, while becoming insignificant over longer time-horizons. Our results are most consistent with the findings of Campbell et al. (2008) in terms of magnitude, while the overarching conclusions are also consistent with Gao et al. (2018).

While distressed portfolios have low average excess returns, they have puzzlingly high market betas and loadings on SMB and HML. When regressing against the Fama-French five-factors, we find that portfolios with more distressed stocks have negative loadings on the RMW and CMA factors. These findings are consistent with the observed portfolio characteristics. As such, a partial explanation for their poor performance is explained by low operating profitability and aggressive investment. This suggests that one should make use of the Fama-French five-factor model when evaluating the performance of distressed stocks.

We acknowledge that a limitation with our study may be the smaller sample size. Due to constrained accounting data availability, we lose a number of observation when computing our Distance-to-Default measure. Furthermore, our sample seem to behave slightly different than the general market, considering our small stocks averaged lower returns than large stocks, which will have a significant impact on our results as small stocks are highly prevalent in the lowest decile portfolio. Another issue is the restricted access to Moody's KMV Expected Default Frequencies measure, which might deliver more accurate predictions of default and thus a better proxy for financial distress risk. However, we find that our results are similar to previous studies using larger datasets. Thus, these effects are likely to have had low impact on the aggregated results.

It is important to note that the additional factors of the Fama-French five-factor model fail to give a full risk-based explanation for the poor returns on distressed stocks. Therefore, further research should investigate other plausible reasons that could explain the anomaly. We hypothesize that market inefficiencies, such as short-selling restrictions or limited coverage and information on small stocks, could provide some explanation. Could these factors restrict the possibility to take advantage of the anomaly? Additionally, it would be interesting to investigate the possibility of developing a new asset pricing model that incorporates financial distress risk and test if such a model could more accurately predict expected stock returns in order to be used in practice.

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Appendix

Appendix 1. Distance-to-Default calculation

For the computation of the Distance-to-default measure, Vassalou and Xing (2004) assume that the capital structure of the firm includes both equity and debt. The market value of a firm's assets is assumed to follow a geometric Brownian motion (GBM):

$$dV_A = \mu V_A dt + \sigma_A V_A dW \tag{1}$$

Where V_A is the value of the firm's assets, with an instantaneous drift μ and an instantaneous volatility σ_A. W is a standard Wiener process.

The market value of equity, V_E is given by the Black and Scholes (1973) formula for call options:

$$V_E = V_A N(d_1) - Xe^{-rT} N(d_2) \tag{2}$$

where

$$d_1 = \frac{\ln(V_A/X) + \left(r + \frac{1}{2}\,\sigma_A^2\right)T}{\sigma_A\sqrt{T}}\,, \quad d_2 = d_1 - \sigma_A\sqrt{T} \tag{3}$$

Where X_t is the book value of debt at time t that has maturity equal to T and r is the risk-free rate, and N is the normal cumulative distribution function.

The default probability is defined as the probability that the firm's assets will be less than the book value (X_t) of the firm's liabilities:

$$P_{def,t} = Prob\left(V_{A,t+T} \leq X_t \middle| V_{A,t} = Prob\,(\ln\left(V_{A,t+T}\right) \leq \ln(X_t)\,|V_{A,t}\right) \tag{4}$$

Given that the value of the assets follows the geometric Brownian motion (GBM) of equation (1), the value of the asset at any time t is given by the following:

$$\ln\left(V_{A,t+T}\right) = \ln\left(V_{A,t}\right) + \left(\mu - \frac{\sigma_A^2}{2}\right)T + \sigma_A\sqrt{T_{e_{t+T}}} \tag{5}$$

$$e_{t+T} = \frac{W\,(t+T) - W\,(t)}{\sqrt{T}} \quad and \quad e_{t+T} \sim N(0,1). \tag{6}$$

Thus, the default probability can be rewritten as:

$$P_{def,t} = Prob\ (\ \ln\left(V_{A,t}\right) - \ln(X_t) + \left(\mu\ \ -\ \frac{\sigma_A^2}{2}\right)T + \sigma_A\sqrt{T_{e_{t+T}}} \leq 0\ )$$

$$P_{def,t} = Prob\ (-\frac{\ln\left(\frac{V_{A,t}}{X_t}\right) + \left(\mu\ \ -\ \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}\ \geq\ e_{t+T} \tag{7}$$

Distance-to-default (DD) can be written as:

$$DD_t = \frac{\ln\left(\frac{V_{A,t}}{X_t}\right) + \left(\mu\ \ -\ \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} \tag{8}$$

Finally, the theoretical probability of default can be calculated using the following equation:

$$P_{def} = N(-DD) = N\left(-\ \frac{\ln\left(\frac{V_{A,t}}{X_t}\right) + \left(\mu\ \ -\ \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}\right) \tag{9}$$

Appendix 2. Fama-French factors construction

The factors are constructed following the method of Fama and French (1993, 2015). Below is a brief description of which variables were used from the CRSP and Compustat databases.

The factors for the five-factor model are constructed using 6 value-weight portfolios formed on size (ME) and book-to-market (B/M), 6 value-weight portfolios formed on size (ME) and operating profitability (OP) and 6 value-weight portfolios formed on size and investment (Inv).

The factors for the three-factor model are constructed using only 6 value-weight portfolios on size (ME) and book-to-market (B/M) where market capitalization (ME) is calculated as the closing price times number of shares outstanding: (PRC * SHROUT).

Operating profitability is calculated as annual revenues minus cost of goods sold, interest expense and selling, general and administrative expenses divided by book equity for December of year t-1: ((REVT – COGS – XINT – XSGA)/CEQ).

Investment is calculated as the change in total assets (AT) from year t-2 to year t-1 divided by total assets of year t-2.

The factors are defined as the following:

SMB (small minus big) is the average return on the small stock portfolios minus the average return on the large stock portfolios.

HML (high minus low) is the average return on the value portfolios (high B/M) minus the average return on the growth portfolios (low B/M)

RMW (robust minus weak) is the average return on the robust operating profitability portfolios (high OP) minus the average return on the weak operating profitability portfolios (low OP)

CMA (conservative minus aggressive) is the average return on the conservative investment portfolio (low Inv) minus the average return on the aggressive investment portfolio (high Inv)

Appendix 3. Risk-sorted decile portfolios returns regressed against sample-specific Fama-French factors

As a robustness check, we present similar results as in Table III, but here we present alphas following regressions against our sample-specific Fama-French factors instead of regressing the portfolio returns against the Fama-French five-factors obtained from the Kenneth R. French Data Library. Similar (and significant) results are obtained.

Portfolios	0010	1020	2030	3040	4050	5060	6070	7080	8090	9000
Panel A. Portfolio Alphas										
Mean excess return	5.35%	3.78%	3.81%	-0.25%	-1.05%	-3.56%	-4.97%	-7.34%	-11.93%	-13.18%
	(3.70)**	(3.32)**	(3.23)**	(0.23)	(0.77)	(2.47)*	(3.09)**	(3.69)**	(5.40)**	(4.91)**
CAPM alpha	7.54%	5.10%	3.84%	-0.66%	-1.32%	-4.45%	-6.51%	-9.93%	-14.98%	-16.35%
	(6.76)**	(5.52)**	(3.58)**	(0.60)	(0.96)	(3.12)**	(4.26)**	(5.60)**	(7.82)**	(6.77)**
3-factor alpha	7.67%	5.17%	3.85%	-0.91%	-2.25%	-5.46%	-7.57%	-11.05%	-16.29%	-17.57%
	(7.26)**	(5.90)**	(3.69)**	(0.85)	(1.72)	(4.06)**	(5.33)**	(6.99)**	(9.64)**	(8.11)**
4-factor alpha	6.39%	4.75%	3.87%	-1.10%	-2.45%	-5.05%	-6.57%	-9.73%	-14.56%	-14.57%
	(6.55)**	(5.42)**	(3.66)**	(1.02)	(1.85)	(3.72)**	(4.69)**	(6.32)**	(9.09)**	(7.57)**
5-factor alpha	7.36%	4.79%	3.40%	-1.00%	-1.76%	-5.22%	-7.27%	-10.29%	-15.79%	-16.75%
	(6.79)**	(5.39)**	(3.25)**	(0.94)	(1.34)	(3.82)**	(4.94)**	(6.25)**	(9.04)**	(7.48)**
Panel B. Three-Factor Regression Coefficients										
RMRF	0.700	0.794	0.940	0.995	1.038	1.117	1.192	1.323	1.427	1.418
	(33.22)**	(44.89)**	(44.37)**	(45.12)**	(37.96)**	(39.15)**	(39.18)**	(38.39)**	(37.75)**	(29.05)**
SMB	-14.865	-13.182	-12.391	-1.486	13.467	16.826	24.441	36.242	34.512	49.309
	(5.43)**	(5.73)**	(4.50)**	(0.52)	(3.79)**	(4.54)**	(6.18)**	(8.09)**	(7.03)**	(7.77)**
HML	-0.154	-0.104	-0.055	0.209	0.225	0.296	0.389	0.409	0.632	0.594
	(3.77)**	(3.02)**	(1.33)	(4.88)**	(4.24)**	(5.34)**	(6.59)**	(6.11)**	(8.61)**	(6.26)**
Panel C. Five-Factor Regression Coefficients										
RMRF	0.686	0.779	0.937	1.003	1.050	1.154	1.240	1.357	1.480	1.497
	(31.57)**	(43.24)**	(43.83)**	(45.13)**	(38.11)**	(39.86)**	(39.30)**	(37.87)**	(37.85)**	(29.71)**
SMB	-0.076	-0.092	-0.063	0.004	0.090	0.143	0.159	0.214	0.251	0.382
	(2.85)**	(4.18)**	(2.42)*	(0.16)	(2.67)**	(4.03)**	(4.12)**	(4.89)**	(5.25)**	(6.19)**
HML	-0.146	-0.080	-0.052	0.195	0.202	0.241	0.335	0.376	0.567	0.482
	(3.34)**	(2.22)*	(1.21)	(4.37)**	(3.64)**	(4.13)**	(5.28)**	(5.22)**	(7.22)**	(4.75)**
RMW	0.018	-0.040	-0.017	0.035	0.085	0.066	0.065	-0.016	-0.012	0.073
	(0.42)	(1.13)	(0.40)	(0.79)	(1.57)	(1.16)	(1.04)	(0.23)	(0.16)	(0.73)
CMA	0.061	0.015	0.071	0.060	-0.009	0.064	0.046	-0.140	-0.045	-0.002
	(1.62)	(0.48)	(1.91)	(1.55)	(0.19)	(1.28)	(0.83)	(2.25)*	(0.67)	(0.02)