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Financial distress and idiosyncratic volatility: An empirical investigation

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Abstract

We investigate the link between distress and idiosyncratic volatility. Specifically, we examine the twin puzzles of anomalously low returns for high idiosyncratic volatility stocks and high distress risk stocks, documented by Ang et al. (2006) and Campbell et al. (2008), respectively. We document that these puzzles are empirically connected, and can be explained by a simple, theoretical, single-beta CAPM model.

JEL classification: G11; G12

Keywords: Distress risk; Idiosyncratic volatility; Single-beta CAPM

1. Introduction

According to modern finance theory, high-risk projects should, in equilibrium, offer high returns. Thus, there should be high returns for bearing the elevated risk that is associated with financial distress, bankruptcy, default, and idiosyncratic volatility; however, this is not always the case. Indeed, in some instances, the returns on high-risk stocks are very low, which flies in the face of modern financial theory.

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In this paper, we examine the interaction between distress and idiosyncratic volatility, how this interaction affects the required return, and propose a rational explanation to two related puzzles uncovered by recent research on distress and idiosyncratic volatility. First, Ang et al. (2006) discover that stocks with high idiosyncratic volatility relative to the Fama and French (1993) model earn anomalously low returns. Similarly, there have been parallel findings in another line of research focusing on the effect of bankruptcy (distress) risk on stock returns. For example, Dichev (1998), Griffin and Lemmon (2002), and Campbell et al. (2008) document that stocks with high likelihood of distress receive anomalously low returns. This suggests that some risky (distressed) stocks do not receive compensatory returns.

There is an intuitive reason to believe that these two puzzles are related to each other. According to the Merton (1974) model, corporate debt is a risk-free bond less a put option on the value of the firm's assets, with a strike price equal to the face value of the debt. Thus, a firm with more volatile equity may experience an option effect, as it is more likely to reach the boundary condition for default. Indeed, based on this argument, Campbell and Taksler (2003) show that idiosyncratic firm-level volatility can explain a significant part of cross-sectional variation in corporate bond yields. Given this result, the puzzle that stocks with high idiosyncratic volatility receive anomalously low returns may reflect an option-like effect, and therefore be a component of the distress risk puzzle.

We first investigate the link between the idiosyncratic volatility effect and the distress effect by sequential sorting. We proxy for firms' distress risk by Altman's (1968) *Z*-score and Ohlson's (1980) *O*-score. In our primary exercise, we control for the distress effect by first sorting stocks into quintiles according to their *Z*-score or *O*-score, then within each quintile, sorting again into portfolios based on firms' idiosyncratic volatility. Once we control for distress risk, we find that stocks with high idiosyncratic volatility earn significantly lower returns than low idiosyncratic volatility stocks, mainly in extreme quintiles: those with the lowest or the highest distress risk. In a separate exercise, we sort on distress after controlling for idiosyncratic risk. Similar to the above results, we document that for the most volatile stocks, the largest negative returns always occur at extreme distress quintiles. We also find that across volatility quintiles, the largest value of returns often occur for extremely distressed or extremely healthy quintiles. While intriguing, these latter results are not always statistically significant. The results from our primary exercise above lend support to our conjecture that the idiosyncratic volatility puzzle is closely related to the distress effect. In other words, the idiosyncratic volatility effect exists conditional on distress risk. Hence, our first contribution is to establish a bridge between the idiosyncratic volatility and distress risk puzzles.

After we build this bridge, we move forward to investigate an appealing, rational explanation for the twin puzzles. For this purpose, we apply a methodology based on the work of Ferguson and Shockley (2003). Following the critique of Roll (1977) and Ferguson and Shockley (2003) observe that using an equity-only proxy for the market portfolio will understate equity betas, and that this understatement is an increasing, convex function of firm leverage. Due to this convexity, the beta estimation error should be more pronounced for more distressed firms. It then follows that in the cross-section, the equity beta estimation errors will not be random. They will be systematically related to the relative leverage and relative distress of each firm in the sample. As a result, the model predicts that firm leverage and financial distress will capture the convex beta estimation errors induced by the use of an equity-only market proxy.

Our approach is to apply a corrected single-beta CAPM model to address the issue of anomalously low returns on the most volatile and most distressed stocks. It turns out that when we use the corrected CAPM to adjust stock returns, the spread between high and low volatility stocks, and between high and low distress risk stocks, become insignificantly different from zero. Moreover, the "GRS" test of Gibbons et al. (1989) cannot reject the null hypothesis of jointly zero abnormal returns across the volatility portfolios and distress risk portfolios. The second contribution in our paper, therefore, is to provide a rational explanation to the idiosyncratic volatility puzzle and the distress risk puzzle.

The rest of this paper is organized as follows. Section 2 investigates the link between the idiosyncratic volatility and distress risk puzzles. We do sequential sorting to examine the idiosyncratic volatility effect, controlling for distress risk, and vice versa. In Section 3, we develop a simple, rational explanation for the twin puzzles. Specifically, we use a corrected CAPM model to adjust stock returns and implement joint statistical tests to determine whether the model can explain abnormal returns on idiosyncratic volatility and distress risk portfolios. Section 4 concludes.

2. Empirical relation between idiosyncratic volatility and distress

This section is devoted to studying the link between idiosyncratic volatility and distress in the cross-section of stock returns. We begin by briefly discussing prior empirical research, followed by a description of data and construction of key variables. Then we turn to our sequential sorting procedure, and continue to discuss the results from Fama–French regressions for the sequentially sorted portfolio. We end this section with an analysis of the volatility and distress portfolios. Ang et al. (2006) discover that stocks with high idiosyncratic volatility earn low returns: the return differential between high- and low-idiosyncratic volatility stocks is highly significant and -1.31% per month. This result holds even after controlling for aggregate volatility risk, size, book-to-market, momentum, coskewness, dispersion in analysts' forecasts, and liquidity effects.[1] A parallel finding exists in the distress risk literature. For example, in a dataset of NYSE and AMEX stocks, Dichev's (1998) results indicate that the average return differential between high- and low-distress firms is -0.59% per month.[2] And the results in Campbell et al. (2008) indicate that the average return differential between high and low-distress firms is -19.4% per year.[3] Thus, highly distressed firms earn anomalously low returns.

As mentioned earlier, these puzzles are related to each other. Consider the Merton (1974) formalization of corporate debt as a risk-free bond less a put option on the value of firm assets. Consequently, a firm with more volatile equity is more likely to reach the boundary for default. Developing this logic, Campbell and Taksler (2003) show that idiosyncratic firm-level volatility explains a significant part of cross-sectional variation in corporate bond yields.

We develop this logic even further. In particular, we recognize that stocks with high idiosyncratic volatility have two empirical characteristics and an important theoretical

[1] See Ang et al. (2006), Table VI.

[2] Using a sample of NYSE, NASDAQ, and AMEX firms between 1965 and 1996, Griffin and Lemmon (2002) confirm results similar to Dichev (1998), and provide further evidence that these results are primarily driven by low book-to-market stocks.

[3] See Dichev (1998) Table III, and Campbell et al. (2008) Table VI.

feature. The two empirical characteristics are low returns – from Ang et al. (2006) – and a strong relation to the return on corporate bonds – from Campbell and Taksler (2003). The theoretical feature is that high volatility corresponds to an increased likelihood of default or distress. Combining these theoretical and empirical properties, it is a plausible conjecture that the idiosyncratic volatility puzzle and the distress puzzle are related.

2.1. Definitions and data structure

Our measures of idiosyncratic volatility and distress risk are similar to those used in the literature. We use the same approach as Ang et al. (2006). That is, for each firm with return $r_{i,t}$, we estimate idiosyncratic volatility relative to the Fama and French (1993) model as follows:

$$r_{i,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \varepsilon_{i,t}, \tag{1}$$

where idiosyncratic volatility is $\sqrt{var(\varepsilon_{i,t})}$.

We use the Altman (1968) Z-score and the Ohlson (1980) O-score as measures of distress risk. These two models are popular for bankruptcy prediction and have been widely used in empirical research and practice. For example, Dichev (1998) investigates whether the risk of bankruptcy is a systematic risk using Z-score and O-score. Griffin and Lemmon (2002) also use O-score to examine the relationship between book-to-market ratio of equity, distress risk, and stock returns. The definitions for Z-score and O-score are as follows.

$$\begin{aligned} Z\text{–score} = {} & 1.2\frac{\text{working capital}}{\text{total assets}} + 1.4\frac{\text{retained earnings}}{\text{total assets}} \\ & + 3.3\frac{\text{earnings before interest and taxes}}{\text{total assets}} \\ & + 0.6\frac{\text{market value of equity}}{\text{book value of total liabilities}} + 1.0\frac{\text{sales}}{\text{total assets}}, \end{aligned}$$

$$\begin{aligned} O\text{–score} = {} & -1.32 - 0.407\log(\text{total assets}) + 6.03\frac{\text{total liabilities}}{\text{total assets}} \\ & - 1.43\frac{\text{working capital}}{\text{total assets}} + 0.076\frac{\text{current liabilities}}{\text{current assets}} \\ & - 1.72(1 \text{ if total liabilities} > \text{total assets, else } 0) - 2.37\frac{\text{net income}}{\text{total assets}} \\ & - 1.83\frac{\text{funds from operations}}{\text{total liabilities}} \\ & + 0.285(1 \text{ if net loss for last two years, else } 0) \\ & - 0.521\frac{\text{net income}_t - \text{net income}_{t-1}}{|\text{net income}_t| + |\text{net income}_{t-1}|}. \end{aligned}$$

From the above definitions, Z-score measures financial strength; a higher Z-score means a lower probability of bankruptcy. Conversely, O-score measures financial distress; a higher O-score means a higher probability of bankruptcy.

Table 1
Summary statistics.

Statistics	O-score	Z-score	IV	Leverage
Mean	0.43	93.96	3.59	1.48
Winsorized mean	−0.62	10.85	3.43	1.10
Median	−0.83	3.99	2.93	0.60
Std Dev	301.11	2716.76	2.65	6.32
Min	−2908.80	−4358.39	0.00	0.00
Max	118,268.34	425,271.00	126.73	948.25
# of Obs	155,019	130,069	156,620	139,216

The table presents statistics from our sample. The time period is 1964–2006. O-score and Z-score are as defined in Section 2 of the text. IV denotes idiosyncratic volatility, as defined from Eq. (1). Leverage is computed as in the appendix.

Both Altman's (1968) and Ohlson's (1980) models are derived for industrials, so our broadest sample consists of all industrial firms available simultaneously on the NYSE and AMEX CRSP tapes, and the Compustat annual industrial and research tapes for the period 1964–2006. The number of observations is 155,019 firms for O-score, 130,069 for Z-score, and 156,620 for idiosyncratic volatility. The pre-1980 and post-1980 parts of our sample are expected to differ, since the latter sample contains substantially more CRSP-Compustat matched firms. Research by Altman (1993) and Dichev (1998) shows that the rate of insolvency and business failure has dramatically increased since about 1980. We therefore display subsample results, where relevant.

2.2. Key features of the data

The data we use are from CRSP and Compustat, with specific details documented in the appendix. Table 1 summarizes the data. In most cases, the standard deviation is large relative to the mean, indicating substantial variation in much of the data. Table 2 reports the correlations among the key variables. Panel A presents cross-sectional correlations for all years of data combined. The largest correlation is approximately 14%, between O-score and leverage. The smallest correlation is 0.06%, between Z-score and idiosyncratic volatility. The p-values are all less than 0.05, indicating that all our variables are correlated at the 5% significance level. Average cross-sectional correlations are presented in Panel B.[4] The most significant finding is that the correlations are appreciably higher than in the preceding panel. For example, the correlation between O-score and leverage is approximately twice as large as those in Panel A, at 27.71%. In sum, the correlations across our key variables are economically or statistically significant.

2.3. Analysis of idiosyncratic volatility, controlling for distress

As argued earlier, distress and volatility may be plausibly related. To examine whether the idiosyncratic volatility effect differs from the distress risk effect, we do sequential

[4] p-Values are not presented because they would involve averages of the annual p-values, which are not easily interpretable.

Table 2
Correlations.

	O-score	*Z*-score	IV	Leverage
Panel A: cross-sectional correlations				
O-score	1.0000	−0.0100	0.0069	0.1374
		(0.0003)	(0.0069)	(<0.0001)
Z-score		1.0000	0.0060	−0.0076
			(0.0314)	(0.0094)
IV			1.0000	0.0907
				(<0.0001)
Leverage				1.0000
				(<0.0001)
Panel B: cross-sectional correlations, averaged over 1964–2006				
O-score	1.0000	−0.1076	0.2493	0.2771
Z-score		1.0000	−0.0039	−0.0595
IV			1.0000	0.1180
Leverage				1.0000

The table presents correlations for each variable. Panel A shows pooled correlations, while Panel B shows correlations, averaged over the sample period. The time period is 1964–2006. *O*-score and *Z*-score are as defined in Section 2 of the text. IV denotes idiosyncratic volatility, as defined from Eq. (1). Leverage is computed as in the appendix. *p*-Values are in parentheses.

sorting on distress risk and idiosyncratic volatility of the sample firms. Specifically, we examine whether the idiosyncratic volatility puzzle exists in all distress risk quintiles. The bankruptcy scores are computed from Compustat data as of the fiscal year-end of a given year t. To ensure that the accounting data are available to calculate the distress risk measures, we delay the bankruptcy scores by six months. In June of each year, stocks are first ranked into five distress quintiles according to their previous December *Z*-score/*O*-score. Within each distress quintile, firms are then sorted into five groups according to their idiosyncratic volatility from Eq. (1), using daily data in the past year. For July of t through June of $t+1$, the return on each portfolio is calculated as the value-weighted average return of the stocks in the portfolio. Table 3 presents the idiosyncratic volatility effect, controlling for distress risk. Panel A presents the sorting results using *Z*-score, while Panel B uses *O*-score sorting. Monthly abnormal returns relative to the Fama and French (1993) three-factor model are reported in percentages.

First, in the first row of Panel A in Table 3, labelled "single sorted portfolios," a significantly negative abnormal return is observed for the highest IV portfolios. Similarly, the difference in abnormal return between the highest and the lowest IV quintiles, or 5-1, is also negative and significant. This corroborates the results of Ang et al. (2006). Now, let us turn to the effect of distress. From Panel A, sorting on *Z*-score does not affect the importance of high-volatility portfolios. Across *Z*-quintiles, only the high volatility portfolios ($IV = 5$) receive significant abnormal returns in multiple cases. Further, the largest 5-1 differentials are for the most healthy ($Z = 5$) or most distressed ($Z = 1$) portfolios. In Panel B, the distress quintile with the largest number of significant, negative returns is that of highest distress ($O = 5$). Moreover, the largest abnormal returns in absolute value are always for the most distressed ($O = 5$) firms. Except for the least volatile

Table 3
Idiosyncratic volatility, controlling for distress.

Single sorted portfolios	Low = 1		IV		High = 5	5-1
	0.06	−0.04	−0.05	−0.27	−0.60	−0.66
	(1.52)	(0.60)	(0.45)	(2.02)	(2.51)	(2.52)
Panel A: portfolios sorted on idiosyncratic volatility (IV) within Z-score quintiles						
Low = 1	−0.10	−0.21	−0.11	−0.19	−0.94	−0.85
	(0.88)	(1.41)	(0.54)	(0.80)	(3.19)	(2.49)
	−0.08	−0.30	−0.38	−0.23	−0.53	−0.45
	(0.91)	(2.36)	(2.53)	(1.36)	(2.20)	(1.65)
Z-score	0.12	−0.16	0.09	−0.22	−0.31	−0.44
	(1.18)	(1.68)	(0.56)	(1.30)	(1.51)	(1.84)
	0.12	0.09	−0.02	−0.05	−0.42	−0.54
	(1.35)	(0.93)	(0.13)	(0.30)	(1.56)	(1.75)
High = 5	0.15	0.27	−0.01	−0.56	−1.01	−1.16
	(1.48)	(1.71)	(0.03)	(2.75)	(3.45)	(3.57)
Panel B: portfolios sorted on idiosyncratic volatility (IV) within O-score quintiles						
Single sorted portfolios	Low = 1		IV		High = 5	5-1
	0.07	0.03	0.03	−0.19	−0.66	−0.74
	(2.07)	(0.43)	(0.25)	(1.29)	(2.75)	(2.88)
Low = 1	0.13	0.19	0.26	0.08	−0.26	−0.39
	(2.08)	(1.58)	(1.40)	(0.41)	(1.17)	(1.72)
	0.11	−0.03	−0.06	0.20	−0.04	−0.16
	(1.43)	(0.37)	(0.43)	(1.05)	(0.17)	(0.53)
O-score	−0.13	0.08	−0.15	−0.29	−0.38	−0.25
	(1.56)	(0.75)	(1.17)	(1.80)	(1.42)	(0.86)
	−0.03	−0.12	0.11	−0.17	−0.44	−0.41
	(0.28)	(1.05)	(0.78)	(0.98)	(1.64)	(1.24)
High = 5	0.22	−0.38	−0.38	−0.96	−1.41	−1.63
	(1.32)	(2.28)	(1.47)	(3.37)	(4.83)	(4.73)

The table presents percentage abnormal returns on idiosyncratic volatility (IV) portfolios. Abnormal returns are adjusted by the Fama and French (1993) model, with associated robust Newey and West (1987) t-statistics in parentheses. Panel A presents idiosyncratic volatility portfolio returns controlling for Z-score. In the "Single sorted portfolios" row, each June firms are sorted into five quintiles according to their idiosyncratic volatility from Eq. (1) using daily data in the past year. In the 10 rows beneath, in June of each year, stocks are first sorted into five quintiles according to their previous December Z-score. Within each quintile, stocks are then sorted into five groups on the basis of their idiosyncratic volatility for the past year. Portfolios are value-weighted. The column "5-1" refers to the difference in monthly abnormal returns between portfolio 5 (the portfolio of stocks with highest idiosyncratic volatility) and portfolio 1 (the lowest idiosyncratic volatility portfolio). Panel B repeats the same procedure using O-score. The sample period is from 1964 to 2006.

stocks (IV = 1), the largest negative returns occur for the most distressed stocks ($O = 5$), and the largest 5-1 differential is for the most distressed stocks.[5]

[5]In order to obtain further information on the pricing patterns over our data sample, we examine subsamples 1964–1981 and 1981–2006. These results are quite similar, and available upon request from the authors.

2.4. Analysis of distress, controlling for idiosyncratic volatility

By reversing the sorting order, we can assess whether the distress risk effect prevails in the presence of idiosyncratic volatility. For this experiment, in June of each year, we first sort stocks into five portfolios according to their idiosyncratic volatility in the past year. Within each quintile portfolio, we then sort stocks into five groups based on their previous December Z-score or O-score. Portfolios are held through the next June and returns are value weighted.

Table 4 presents the results. From Panel A, observe that the largest negative abnormal returns are generally for the highest volatility portfolios, within each distress quintile. Also, for the highest volatility quintiles (IV = 4 or 5), the largest negative returns are always in the highest Z-quintile. Moreover, across volatility quintiles, the largest returns are usually in an extreme distress quintile ($Z = 1$ or 5). However, these are not always statistically significant. Panel B shows the same analysis, using O-score. Here, across distress quintiles, the largest negative returns are always for the highest volatility stocks (IV = 5). For the highest volatility quintiles (IV = 4 or 5), the largest absolute value returns are at an extreme distress quintile, $O = 5$. And the largest, most significant 5-1 differential is for the highest volatility stocks.[6]

To summarize Tables 3 and 4, there seem to be strong interactions between volatility and distress at the extreme quintiles. In particular, since the largest significant spreads in Table 3 always occur at extreme distress quintiles, we may say that the idiosyncratic volatility effect has a tendency to occur conditionally on distress.

2.5. Characteristics of volatility and distress portfolios

The preceding subsection has presented material on the return characteristics of portfolios that are sorted on idiosyncratic volatility and distress. It is also interesting to analyze the volatility and distress properties of these portfolios. Such properties are presented in Table 5.

We first discuss Panel A of Table 5, which shows the characteristics of portfolios sorted on idiosyncratic volatility. The first seven columns from the left in this panel present the value-weighted Z-score and idiosyncratic volatility of our 5×5 sorted portfolios, where sorting is first done on distress risk. In the top five rows, notice that for the most distressed stocks ($Z = 1$), there is a monotonic increase in distress (decrease in Z) with volatility. In the next five rows, notice that the level of idiosyncratic volatility is generally largest, with a single exception, at one of the extreme Z-quintiles. We now turn to the last seven columns in Panel A, which repeat the same procedure using O-score. Looking again at the top five rows, we see that except for the most distressed stocks ($O = 5$), the greatest degree of health (lowest O) is for the low volatility stocks (IV = 1). The next five rows show another pattern: in almost every case, volatility increases monotonically with distress (O-score), and volatility is always largest for the highest distress stocks.

Panel B of Table 5 shows characteristics of portfolios sorted on distress, while controlling for idiosyncratic volatility. The first seven columns from the left in this panel present the value-weighted Z-score and idiosyncratic volatility of our 5×5 Z-score sorted portfolios, where sorting is first done on idiosyncratic volatility. We see from the top first

[6] Subsample results are quite similar, and available upon request from the authors.

Table 4
Distress risk, controlling for idiosyncratic volatility.

Single sorted portfolios	Low = 1		Z-score		High = 5	1-5
	−0.09	−0.18	0.06	0.09	0.11	−0.20
	(1.13)	(2.26)	(0.76)	(1.38)	(1.42)	(1.69)
Panel A: portfolios sorted on Z-score, within idiosyncratic volatility (IV) quintiles						
Low = 1	−0.14	−0.07	0.15	0.06	0.18	−0.32
	(1.18)	(0.88)	(1.50)	(0.74)	(1.97)	(2.16)
	−0.22	−0.33	−0.18	0.11	0.21	−0.43
	(1.58)	(2.79)	(1.69)	(1.00)	(1.76)	(2.18)
IV	−0.38	−0.22	−0.02	0.00	0.16	−0.54
	(2.48)	(1.74)	(0.08)	(0.00)	(0.89)	(2.36)
	−0.06	−0.11	−0.39	−0.20	−0.62	0.56
	(0.29)	(0.63)	(2.86)	(1.13)	(2.91)	(2.13)
High = 5	−0.76	−0.59	−0.25	−0.50	−0.97	0.21
	(2.71)	(2.17)	(1.08)	(1.71)	(3.26)	(0.65)
	Low = 1		O-score		High = 5	5-1
Single sorted portfolios	0.12	0.05	−0.13	−0.11	−0.29	−0.41
	(2.11)	(0.96)	(2.18)	(1.50)	(1.98)	(2.64)
Panel B: portfolios sorted on O-score, within idiosyncratic volatility (IV) quintiles						
Low = 1	0.11	0.11	0.04	−0.05	0.09	−0.02
	(1.79)	(1.88)	(0.56)	(0.59)	(0.87)	(0.16)
	0.19	0.09	−0.13	0.05	−0.02	−0.21
	(1.56)	(1.11)	(1.28)	(0.47)	(0.12)	(1.00)
IV	0.08	0.09	−0.13	−0.13	0.03	−0.06
	(0.47)	(0.53)	(0.79)	(0.91)	(0.17)	(0.24)
	−0.05	−0.20	−0.14	−0.19	−0.52	−0.47
	(0.25)	(0.98)	(0.68)	(1.27)	(2.65)	(1.87)
High = 5	−0.43	−0.69	−0.32	−0.82	−1.15	−0.71
	(1.64)	(2.70)	(0.97)	(2.59)	(3.55)	(2.52)

The table presents percentage abnormal returns on portfolios that are sorted according to their degree of distress, as measured by Z-score and O-score. Abnormal returns are adjusted by the Fama and French (1993) model, with associated robust Newey and West (1987) t-statistics in parentheses. Panel A presents portfolio returns for distress risk (proxied by Z-score) controlling for idiosyncratic volatility. In the row "single sorted portfolios," each June, firms are sorted into five quintiles according to their previous December Z-score. In the succeeding 10 rows, stocks are first sorted into five quintiles each June based on their idiosyncratic volatility for the past year. Within each quintile, stocks are then sorted into five groups according to their previous December Z-score. Portfolios are value-weighted. The column "1-5" refers to the difference in monthly abnormal returns between portfolio 1 (the portfolio of stocks with highest distress risk) and portfolio 5 (the lowest distress risk portfolio). Panel B repeats the same procedure using O-score. The sample period is from 1964 to 2006.

five rows that distress is always largest (Z is smallest) at an extreme volatile quintile, IV = 1 or IV = 5. Moreover, from the bottom five rows, observe that for the most volatile stocks (IV = 5), volatility increases monotonically with distress.[7] We now turn to the last seven columns. Here we see from the top five rows that in all cases, distress (O-score)

[7]Recall that lower Z quintiles correspond to higher distress.

Table 5
Characteristics of 5 × 5 distress and idiosyncratic volatility portfolios.

Panel A: characteristics of IV portfolios, controlling for distress

	Portfolios sorted on IV within Z-score quintiles						Portfolios sorted on IV within O-score quintiles				
	Low = 1		IV		High = 5		Low = 1		IV		High = 5
Z values						*O values*					
Low = 1	1.47	1.40	1.17	0.70	−0.26	Low = 1	−3.42	−3.26	−3.34	−3.41	−3.34
	2.81	2.82	2.79	2.80	2.78		−1.83	−1.82	−1.78	−1.79	−1.76
Z-score	4.35	4.35	4.32	4.31	4.27	Z-score	−0.90	−0.90	−0.89	−0.83	−0.84
	7.68	7.48	7.64	7.70	7.66		−0.02	0.04	0.08	0.12	0.14
High = 5	119.07	428.83	1506.16	541.65	795.68	High = 5	1.90	1.86	2.40	2.81	4.66
IV values						*IV values*					
Low = 1	1.09	2.03	3.15	4.44	7.11	Low = 1	1.18	1.87	2.39	2.97	4.10
	1.31	1.98	2.67	3.49	5.23		1.25	1.84	2.39	3.09	4.37
Z-score	1.29	1.91	2.49	3.22	4.70	Z-score	1.25	1.88	2.49	3.25	4.69
	1.23	1.88	2.44	3.19	4.66		1.41	2.21	2.96	3.85	5.57
High = 5	1.29	2.19	2.82	3.56	5.01	High = 5	1.93	3.24	4.24	5.37	8.02

Panel B: characteristics of distress portfolios, controlling for IV

	Portfolios sorted on Z-score within IV quintiles						Portfolios sorted on O-score within IV quintiles				
	Low = 1		Z-score		High = 5		Low = 1		O-score		High = 5
Z values						*O values*					
Low = 1	1.37	2.47	4.00	6.29	41.05	Low = 1	−3.56	−2.21	−1.44	−0.69	0.39
	1.87	3.26	4.68	7.54	373.94		−3.55	−2.13	−1.39	−0.65	0.60
IV	1.66	3.25	4.84	8.93	401.34	IV	−3.44	−1.94	−1.08	−0.24	1.18
	1.25	2.99	4.72	10.93	2429.16		−3.12	−1.49	−0.55	0.38	2.52
High = 5	−0.75	1.91	3.51	8.15	693.84	High = 5	−2.44	−0.47	0.57	1.70	5.80
IV Values						*IV Values*					
Low = 1	1.13	1.24	1.30	1.25	1.19	Low = 1	1.20	1.27	1.28	1.30	1.36
	1.96	1.95	1.96	1.96	1.98		2.04	2.03	2.05	2.05	2.08
IV	2.67	2.66	2.67	2.66	2.67	IV	2.75	2.77	2.77	2.79	2.81
	3.59	3.55	3.55	3.52	3.53		3.62	3.66	3.66	3.70	3.79
High = 5	5.93	5.43	5.33	5.23	5.19	High = 5	5.25	5.35	5.52	5.78	6.20

The table presents both distress and volatility characteristics of portfolios that are sorted in two ways: first, sorted on idiosyncratic volatility (IV) while controlling for distress; and second, sorted on distress while controlling for idiosyncratic volatility. Panel A presents the results from sorting on idiosyncratic volatility. The first seven columns of Panel A show the distress and idiosyncratic volatility characteristics of 5 × 5 Z-score and idiosyncratic volatility sorted portfolios. In June of each year, stocks are first sorted into five quintiles according to their previous December Z-score. Within each quintile, stocks are then sorted into five groups on the basis of their idiosyncratic volatility for the past year. Value-weighted Z-score and idiosyncratic volatility for each portfolio are reported in the table. The last seven columns of Panel A repeat the same procedure using O-score. Similarly, in Panel B the first seven columns show the distress and idiosyncratic volatility characteristics of 5 × 5 idiosyncratic volatility and Z-score sorted portfolios. The last seven columns of Panel B show the same procedure using O-score. The sample period is from 1964 to 2006.

increases with volatility. From the bottom five rows, in all but one case, volatility increases with distress (O-score). Furthermore, for the bottom five rows, the highest volatility always occurs in the most distressed ($O = 5$) stocks.

To summarize Table 5, there seem to be striking interactions between distress and idiosyncratic volatility, especially for extremely healthy or extremely distressed stocks. In both this table and in a subsample analysis, we find that there is some tendency for distress and volatility to occur in similar sets of firms over long subperiods of our sample.[8]

3. Rational interpretation of idiosyncratic volatility and distress risk

We now investigate an intuitive explanation for the twin puzzles. For simplicity, we will call this an ‘‘equity-bias argument.’’ This section is closely based on the work of Ferguson and Shockley (2003). In their Proposition 1, these researchers prove that under weak conditions, using an equity-only proxy for the market portfolio will understate equity betas, with the error increasing in firm leverage. Thus, firm-specific variables that correlate with leverage will spuriously explain returns after controlling for the proxy beta, by virtue of capturing the missing beta risk.[9] A major impetus for our adopting this approach is the Ferguson and Shockley (2003, p. 2559) suggestion, based on their Proposition 2, that ‘‘Prime candidates for anomaly status are ... firm-specific variables that are strongly related to leverage and distress in the cross-section.’’ Thus, in addition to our empirical results above, given the significant correlations between idiosyncratic volatility and leverage from Table 2, we believe that the idiosyncratic volatility and distress puzzles could fit this profile.

Therefore, this section of our paper can be seen as an application of the Ferguson and Shockley (2003) model to a novel setting. Although our approach builds directly on their framework, our application differs in several important ways. First, we apply their approach ‘‘out of sample.’’ We use the term out of sample because the puzzles we address obtain on a very different data set from what Ferguson and Shockley studied, namely, our distress and idiosyncratic volatility portfolios. Second, our application provides a sense of the predictive power of their theory, since the distress and volatility puzzles that we consider were discovered after that paper was published. Third, we provide another chance to use their proposed factors in a time series setting—given the weaker performance of their factors in time series relative to the cross-section. Thus, in addition to coming to grips with the interrelationship between distress and idiosyncratic volatility, this portion of our paper presents an opportunity to assess and cross-validate the Ferguson and Shockley (2003) model's predictive power.

3.1. *Bias in the single-beta CAPM model*

We now outline the modelling framework. We follow the approach of Ferguson and Shockley (2003) throughout, highlighting the most important steps for our application. We also add steps for clarity where deemed necessary for our analysis. Consider a simple

[8]Subsample estimates are available upon request from the authors.

[9]In an empirical application, the authors document that their portfolios formed on leverage and distress can subsume the Fama and French (1993) factors, SMB and HML, in the cross-section, although their time-series results are less encouraging.

continuous-time economy in which the single-beta CAPM prices all real assets, and firms are allowed to finance their real assets with a simple capital structure.[10] Let M denote the market portfolio, which comprises total debt claims D, and total equity claims E. That is, $M = E + D$. Further, let us denote the covariances of firm i with the entire market, with equity and with debt as $\sigma_{i,MKT}$, $\sigma_{i,E}$, and $\sigma_{i,D}$, respectively; and denote the return variances of the market, equity, and debt as σ^2_{MKT}, σ^2_E, and σ^2_D, respectively. By linearity of the covariance operator, the covariance between firm i's equity claim S_i and M ($\sigma_{i,MKT}$) may be expressed as $\sigma_{i,MKT} = E/M\sigma_{i,E} + D/M\sigma_{i,D}$. Hence, the true beta for firm i's equity is

$$\beta_i = \frac{\sigma_{i,MKT}}{\sigma^2_{MKT}} = \frac{E}{M}\frac{\sigma_{i,E}}{\sigma^2_{MKT}} + \frac{D}{M}\frac{\sigma_{i,D}}{\sigma^2_{MKT}}. \tag{2}$$

However, the consequence of ignoring debt in constructing the market portfolio is that firm i's estimated equity beta, $\hat{\beta}_i^E$, becomes

$$\hat{\beta}_i^E = \frac{\sigma_{i,E}}{\sigma^2_E}, \tag{3}$$

which may differ greatly from the true beta β_i, above, particularly for firms with substantial debt finance. Similarly, the debt beta is defined as $\hat{\beta}_i^D = \sigma_{i,D}/\sigma^2_D$. What is the difference between the true beta and the proxy beta? To see this, notice that the proxy beta in Eq. (3) is very similar to the second right-hand-side term in the true beta's expression in (2). Indeed, multiplying the proxy equity and debt betas by $\sigma^2_{MKT}/\sigma^2_{MKT} = 1$ yields

$$\hat{\beta}_i^E = \frac{\sigma_{i,E}}{\sigma^2_{MKT}}\frac{\sigma^2_{MKT}}{\sigma^2_E} \quad \text{and} \quad \hat{\beta}_i^D = \frac{\sigma_{i,D}}{\sigma^2_{MKT}}\frac{\sigma^2_{MKT}}{\sigma^2_D}.$$

Substituting these relations in (2), we obtain

$$\beta_i = \frac{E}{M}\frac{\sigma^2_E}{\sigma^2_{MKT}} \cdot \hat{\beta}_i^E + \frac{D}{M}\frac{\sigma^2_D}{\sigma^2_{MKT}} \cdot \hat{\beta}_i^D.$$

From this relationship, we can write the proxy equity beta as a transformation of the true beta:

$$\hat{\beta}_i^E = \Phi^{-1}[\beta_i - \Omega\hat{\beta}_i^D], \tag{4}$$

where

$$\Phi = \frac{E}{M}\frac{\sigma^2_E}{\sigma^2_{MKT}} \quad \text{and} \quad \Omega = \frac{D}{M}\frac{\sigma^2_D}{\sigma^2_{MKT}}.$$

Eq. (4) suggests that the error in the proxy equity beta $\hat{\beta}_i^E$ comprises two parts. The first part is a systematic scaling error Φ^{-1}. The second part is a firm-specific error $-\Omega\hat{\beta}_i^D$, reflecting firm covariance with debt claims. Following Ferguson and Shockley (2003), we focus on the second, firm-specific error, since it depends on firm leverage, and therefore might explain at least part of pricing puzzles that are related to financial distress or default. The relevance of (4) to our puzzles can be seen from the economically and statistically significant correlations between volatility, distress, and leverage in Table 2.

[10]A simple capital structure comprises equity and debt, where the equity is common stock, and the debt consists of pure discount bonds.

3.2. Consequences of bias, and possible correction

Before proceeding toward an empirical implementation, we need to analyze the behavior of equilibrium excess returns, in terms of both the true and proxy betas. From Eq. (4) it follows that the true beta, β_i, satisfies

$$\beta_i = \Phi\hat{\beta}_i^E + \Omega\hat{\beta}_i^D. \tag{5}$$

Eq. (5) implies that, in our economy, equilibrium excess returns of firm i, $R_i - R^F$, obey the following relationship:

$$R_i - R^F = [R^{MKT} - R^F]\beta_i = \Phi[R^{MKT} - R^F]\hat{\beta}_i^E + \Omega[R^{MKT} - R^F]\hat{\beta}_i^D,$$

where R^{MKT} denotes the gross return on the market portfolio and R^F is the risk-free rate. For ease of interpretation, we can rewrite the above expression. The reason for rewriting is that in our empirical tests we will use time series data, which adds a further t subscript to each asset return. Therefore, to reduce notational burden, redefine excess returns on the firm and the market at period t ($R_{i,t} - R_t^F$, and $R_T^{MKT} - R_t^F$,) in a simpler way: $R_{i,t}^e = R_{i,t} - R_t^F$ and $R_t^{MKT} = R_t^{MKT} - R_t^F$, respectively, where e denotes excess returns on individual firms, for emphasis. Suppressing the time subscripts temporarily, the above expression becomes

$$R_i^e = R^{MKT}\beta_i = \Phi R^{MKT}\hat{\beta}_i^E + \Omega R^{MKT}\hat{\beta}_i^D. \tag{6}$$

Consequently, the alphas, α_i, will be misspecified if empirical researchers perform the standard market regressions, $R_i^e = \alpha_i + \gamma_i\hat{\beta}_i^E + \varepsilon_i$. In their Proposition 2, Ferguson and Shockley (2003) show that the theoretical alphas satisfy

$$\alpha_i = \left[\overline{\beta}^D - \frac{Cov(\hat{\beta}_i^D, \hat{\beta}_i^E)}{Var(\hat{\beta}_i^E)} \cdot \overline{\beta}^E\right]\Omega R^{MKT}, \tag{7}$$

where $\overline{\beta}^D$ and $\overline{\beta}^E$ are cross-sectional averages of $\overline{\beta}_i^D$ and $\overline{\beta}_i^E$, respectively. Eq. (7) shows that significant alphas are consistent with an equilibrium whenever empirical researchers omit debt in their market regressions. Indeed, the alphas will only be zero when

$$\overline{\beta}^D = \frac{Cov(\hat{\beta}_i^D, \hat{\beta}_i^E)}{Var(\hat{\beta}_i^E)} \cdot \overline{\beta}^E.$$

What does this have to do with the volatility and distress puzzles? The answer is that, to the extent that the volatility and distress portfolios omit debt in the market portfolio, the estimated alphas will be systematically biased. This bias is captured by $\Omega\hat{\beta}_i^D$, part of the second term in Eq. (6).[11] The following arguments illustrate an empirical method of removing this bias.

[11] As mentioned before, the first term involves only a systematic scaling factor, Φ, and therefore will not bias the estimates.

3.3. Empirical implementation

Since $\Omega\hat{\beta}_i^D$ is a function of firm leverage and relative distress, a sensible empirical solution is to create portfolios based on relative leverage and relative distress. In light of the above reasoning, portfolios formed on such factors provide the best complements to the equity market index for explaining the cross-section of returns. This is the approach followed by Ferguson and Shockley (2003) in their empirical implementation, and we do likewise. Specifically, to account for the bias term $\Omega\hat{\beta}_i^D$, we construct two portfolios reflecting relative leverage and relative distress, denoted $R_t^{D/E}$ and R_t^Z, respectively. $R_t^{D/E}$ and R_t^Z are the excess returns of two portfolios designed to mimic the part of asset returns associated with relative leverage and relative distress.[12] We will detail their construction below.

With these portfolios, an empirical researcher can, in principle, overcome the equity bias embodied in Eqs. (6) and (7). Using these portfolios in an empirical setting would imply that the (equity-based) CAPM must be augmented in the following way:

$$R_i^e = \alpha_i + \beta_i^M R_t^{MKT} + \beta_i^{D/E} R_t^{D/E} + \beta_i^Z R_t^Z + \varepsilon_{i,t}, \quad t = 1, 2, \ldots, T, \tag{8}$$

where $R_t^{D/E}$ and R_t^Z are as described in the above paragraph. These two terms are designed to remove the equity bias discussed above.[13]

We now say a few words about $R_t^{D/E}$ and R_t^Z. To construct portfolios for $R_t^{D/E}$ and R_t^Z, we use the following procedure. In June of each year t, firms are assigned to one of three book debt-to-market equity (BD/ME) portfolios based on the one-third and two-third percentile breakpoints determined only from the NYSE firms in the sample. Independently and simultaneously, firms are assigned to one of two portfolios: $Z \leq 2.675$ and $Z > 2.675$ according to their previous December Z-scores. Firms with $Z > 2.675$ are predicted to be in the healthy group, while firms with $Z \leq 2.675$ are predicted to be in the distressed group.[14] Only firms with ordinary common equity are used to form the leverage and distress portfolios. The intersection of the two independent sorts results in six debt-to-equity $(D/E)/Z$ portfolios. Portfolios are valued weighted. $R_t^{D/E}$ is then calculated as the simple average return of the two Z portfolios within D/E portfolio 3 (the highly levered firms) minus the simple average return of the two Z portfolios within D/E portfolio 1 (the least levered firms). Similarly, R_t^Z is the simple average return of the three D/E portfolios within Z portfolio 2 (high Z-firms) minus the simple average return of the three D/E portfolios within Z portfolio 1 (low Z-firms). The portfolios are presented in Table 6.

Panel A of Table 6 shows that the portfolios are reasonably similar to each other and to the Fama-French factors, since their means, standard deviations, and extrema are comparable. Panel B shows that the two main portfolios are highly correlated, at a level of nearly 62%. HML and $R^{D/E}$ are correlated at 50%, which is intuitive given that both strongly reflect return premia for leverage. Finally, in Panel C, the regression results show that $R^{D/E}$ linearly varies more than 40% with R^Z, and explains nearly 38% of the linear

[12] These portfolios are identical to those used by Ferguson and Shockley (2003). Please see their paper for more details.

[13] Further details are in a web appendix, available upon request from the authors.

[14] We choose the cutoff level of 2.675 since it is recommended by Altman (1968) to minimize total type I and type II errors.

Table 6
Relationship of R^Z and $R^{D/E}$ portfolios.

Variable	Mean	Std Dev	Minimum	Maximum
Panel A: summary statistics				
$R^{D/E}$	0.004	0.041	−0.371	0.149
R^Z	0.003	0.028	−0.237	0.081
SMB	0.003	0.032	−0.166	0.219
HML	0.004	0.029	−0.127	0.137
	$R^{D/E}$	R^Z	SMB	HML
Panel B: correlation of factors				
$R^{D/E}$				
R^Z	0.616			
	(<0.001)			
SMB	−0.006	0.089		
	(0.886)	(0.045)		
HML	0.506	−0.081	−0.279	
	(<0.001)	(0.067)	(<0.001)	
R^{Z-}	0.001	0.000	0.117	−0.498
	(0.974)		(0.008)	(<0.001)
Panel C: results of regression $R^Z = \alpha + \beta R^{D/E} + \varepsilon$				
		α	0.002	
			(0.087)	
		β	0.411	
			(<0.001)	
		Adjusted R^2	0.378	

The table presents summary statistics, correlations, and regression results for R^Z, $R^{D/E}$, and R_t^{Z-}. The latter, R_t^{Z-}, is the orthogonalized return spread between high and low Z portfolios. The sample size is 516. Panel A shows summary statistics. Panel B shows correlations. Panel C shows regression results. p-Values are in parentheses.

variation in R^Z. Given such high correlations, we need to go a step beyond the basic Ferguson and Shockley (2003) specification and orthogonalize our mimicking portfolios.[15] We orthogonalize our portfolios by regressing R^Z on $R^{D/E}$, and then collecting the residual, which we denote as R^{Z^-}. We will use this orthogonalized portfolio, R^{Z^-}, in our asset pricing tests below.

3.4. Testing idiosyncratic volatility and distress risk portfolios

Recall that in the previous section, we documented that the idiosyncratic volatility effect exists conditional on high distress risk. We now use the corrected CAPM from the section above to test a simple rational explanation for the distress and idiosyncratic volatility puzzles.

Specifically, if model (8) can explain the idiosyncratic volatility and distress risk puzzles, then the regression intercepts α_i should be zero if we run time-series regression tests on idiosyncratic volatility and distress risk portfolios. For this purpose, we use the GRS test of Gibbons et al. (1989). If the errors are i.i.d. over time, homoscedastic, and independent

[15]Note that in their final step that Ferguson and Shockley (2003) also orthogonalize their mimicking portfolios.

of the factors f, the asymptotic joint distribution of the intercepts gives the test statistic,

$$T\left[1+\left(\frac{E_T(f)}{\hat{\sigma}(f)}\right)^2\right]^{-1}\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}\sim\chi^2_N,$$

where $E_T(f)$ and $\hat{\sigma}(f)$ denote the sample mean and variance of the factors, α is a vector of regression intercepts, Σ is the covariance matrix of regression residuals, and N is the number of assets. For robustness, we also use a finite-sample exact F-test, which we now describe. When the errors are also normally distributed, a multivariate, finite-sample counterpart statistic is:

$$\frac{T-N-K}{N}(1+E_T(f)'\hat{\Omega}^{-1}E_T(f))^{-1}\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}\sim F_{N,T-N-K},$$

where Ω is the covariance matrix of factors and K is the number of factors.

Table 7 presents the GRS test results on the idiosyncratic volatility and distress risk portfolios. To form these portfolios, in June of each year, we sort stocks into five quintiles separately according to their previous December bankruptcy scores (Z-score/O-score) and their idiosyncratic volatility—computed from Eq. (1) using the past year's daily data. Panel A provides evidence of the idiosyncratic volatility puzzle. In the row labelled FF-α, we see that high volatility stocks earn significantly lower Fama–French adjusted returns than do low idiosyncratic volatility stocks. The spread is 0.66% per month, with a t-statistic of 2.52. Moreover, the GRS tests are marginal: one could accept or reject the null hypothesis of jointly zero abnormal returns at the 5% level. When we use the corrected single-beta CAPM (8) to adjust the returns, however, the spread between high and low idiosyncratic volatility stocks becomes insignificantly different from zero. This model's adjusted α is 0.48% per month, with a t-statistic of 1.47. Checking the loadings on the regressands, we can see that the key to interpreting the idiosyncratic volatility puzzle is firm leverage. Loadings on $R^{D/E}$ are in most cases significantly different from zero, decreasing monotonically from low to high volatility stocks. The pattern of loadings on R^{MKT} indicate exacerbation of the volatility effect. Specifically, loadings on R^{MKT} actually monotonically increase from low to high volatility stocks. In support of the equity-bias arguments outlined above, this evidence suggests that firm leverage manages to capture the estimation errors induced by the use of an equity-only market proxy. Both the GRS F-test and χ^2-test have large p-values, in excess of 0.6. This shows that we cannot reject the hypothesis of jointly zero abnormal returns across the idiosyncratic volatility portfolios. Thus, the corrected single-beta CAPM does a very good job of explaining the idiosyncratic volatility effect.

In Panel B of Table 7, distressed stocks (low Z-score) have lower Fama–French adjusted returns, although these are not significant. The spread between low and high Z-score stocks is −0.2% per month. When we use the corrected single-beta CAPM (8) to adjust stock returns, the spread between high and low is only −0.003% per month. GRS tests are roughly similar in both cases. Again, we do not accord much attention to this panel, since the data do not constitute an anomaly, given the insignificance of abnormal returns. Panel C presents similar results for distress risk, using O-score. In this panel, the results are even stronger than for the volatility portfolios discussed above. For the Fama–French model, the spread is 0.41% per month, with a t-statistic of 2.64. Both GRS statistics have minute p-values, indicating that abnormal returns are jointly statistically significant at the 5% level. By contrast, for the corrected CAPM model, the spread is reduced by nearly

Table 7
GRS test on volatility and distress portfolios.

	Low = 1		IV		High = 5	5-1	GRS-F	GRS-χ
FF-α	0.06	−0.04	−0.05	−0.27	−0.60	−0.66	2.14	11.06
	(1.52)	(0.60)	(0.45)	(2.02)	(2.51)	(2.52)	(0.059)	(0.050)
Panel A: portfolios sorted on idiosyncratic volatility (IV)								
α	0.05	−0.02	−0.04	−0.19	−0.43	−0.48	0.676	3.43
	(0.95)	(0.37)	(0.27)	(1.01)	(1.50)	(1.47)	(0.641)	(0.634)
β^{MKT}	0.82	1.16	1.40	1.54	1.59	0.77		
	(39.42)	(69.90)	(37.26)	(27.45)	(20.36)	(8.17)		
βD/E	0.06	−0.02	−0.10	−0.12	−0.28	−0.33		
	(2.72)	(1.22)	(2.85)	(2.25)	(2.85)	(2.88)		
βZ−	−0.02	0.07	0.16	0.09	0.23	0.25		
	(0.44)	(2.01)	(2.11)	(0.81)	(1.38)	(1.26)		
	Low = 1		Z-score		High = 5	1-5	GRS-F	GRS-χ
FF-α	−0.09	−0.18	0.06	0.09	0.11	−0.20	2.34	12.07
	(1.13)	(2.26)	(0.76)	(1.38)	(1.42)	(1.69)	(0.047)	(0.034)
Panel B: portfolios sorted on Z-score								
α	−0.03	−0.05	0.14	0.08	−0.03	−0.003	2.26	11.43
	(0.66)	(0.67)	(1.82)	(1.32)	(0.40)	(0.03)	(0.049)	(0.043)
β^{MKT}	0.89	1.05	1.01	0.95	0.97	−0.08		
	(69.23)	(46.98)	(49.15)	(48.81)	(45.55)	(3.15)		
βD/E	0.20	0.12	0.03	0.03	−0.14	0.34		
	(12.83)	(4.98)	(1.24)	(0.90)	(6.00)	(11.96)		
βZ−	−0.83	−0.48	−0.01	0.23	0.52	−1.35		
	(31.31)	(10.47)	(0.32)	(5.62)	(10.85)	(24.37)		
	Low = 1		O-score		High = 5	5-1	GRS-F	GRS-χ
FF-α	0.12	0.05	−0.13	−0.11	−0.29	−0.41	3.17	16.38
	(2.11)	(0.96)	(2.18)	(1.50)	(1.98)	(2.64)	(0.008)	(0.006)
Panel C: portfolios sorted on O-score								
α	0.02	0.09	−0.07	0.01	−0.19	−0.21	1.78	9.00
	(0.37)	(1.65)	(1.16)	(0.09)	(1.07)	(1.09)	(0.116)	(0.109)
β^{MKT}	0.94	1.00	1.04	1.13	1.37	0.43		
	(62.87)	(53.66)	(53.75)	(39.27)	(31.02)	(8.32)		
βD/E	−0.12	0.05	0.13	0.12	−0.06	0.05		
	(5.59)	(2.74)	(6.49)	(4.34)	(1.08)	(0.90)		
βZ−	0.32	−0.01	−0.36	−0.32	−0.02	−0.33		
	(8.84)	(0.23)	(10.10)	(6.98)	(0.18)	(3.22)		

The table reports results from the "GRS" F and χ^2 tests (GRS-F and GRS-χ) of Gibbons et al. (1989), with associated p-values. These tests assess the joint statistical significance of the alphas for all quintiles. The table also presents intercept estimates from the Fama–French model (FF-α), as well as intercept and coefficient estimates from the regression model $R_i^e = \alpha_i + \beta_i^{MKT} R_t^{MKT} + \beta_i^{D/E} R_t^{D/E} + \beta_i^Z R_t^{Z^-}$, for each quintile i, where R_t^{MKT} is the market excess return, $R_t^{D/E}$ is the return spread between high and low D/E portfolios, and $R_t^{Z^-}$ is the orthogonalized return spread between high and low Z portfolios. Robust Newey and West (1987) t-statistics are in parentheses below these estimates. The column "5-1" refers to the return difference between portfolios 5 and 1. Panel A presents results for idiosyncratic volatility portfolios. Panels B and C present results for Z-score and O-score portfolios, respectively. The sample period is from 1964 to 2006.

one-half, to 0.21% per month, and is no longer significant. Both GRS tests have large *p*-values, indicating that abnormal returns are jointly insignificant. When we examine the pattern of loadings, we see that loadings on the market increase monotonically with distress, and leverage is almost always significant.[16]

To summarize the results of our GRS tests, the above evidence shows that after we correct the beta errors in the CAPM, the model explains the idiosyncratic volatility and distress risk effects. We therefore suggest that the corrected CAPM approach provides a possible rational explanation to the idiosyncratic volatility and distress risk puzzles.

4. Conclusions

This paper investigates the link between the idiosyncratic volatility puzzle and the distress risk puzzle, and proposes a simple, rational explanation for both puzzles. We have two main contributions. Our first contribution is to document an empirical link between distress risk and volatility risk. Sequential sorting indicates that after controlling for distress risk, stocks with high idiosyncratic volatility earn significantly low returns primarily in the highest or lowest distress risk quintile. This implies that the idiosyncratic volatility effect exists conditional on distress risk. Moreover, an analysis of the portfolio characteristics reveal that stocks which are extremely susceptible to or resilient to distress often coincide with those in the extreme volatility quintiles. Thus, there seems to be a complex interaction between distress and idiosyncratic volatility.

Our second contribution is to show that both the idiosyncratic volatility and distress risk puzzles can be explained by a rational theoretical model, based on that of Ferguson and Shockley (2003). Statistical tests show that the corrected model removes abnormal returns for portfolios formed on idiosyncratic volatility and distress risk.

Why should we care about these results? From an asset pricing viewpoint, the reason is that we have made progress toward clarifying the role of distress risk raised in the model of Fama and French (1993). Specifically, our contribution is that we develop and test an empirical model of distress risk that is grounded in a theoretical framework of the CAPM. From an investment perspective, the importance of our results is that we have clarified an empirical link between volatility and distress risk. This may be valuable for risk managers who wish to control exposure to financial distress.

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Appendix A. Variable description and calculation

Book value of equity: Total stockholder's equity (Data 216) + deferred taxes (Data 74) + investment tax credit (Data 208) − preferred stock redemption value (Data 56).[17] If

[16]In order to obtain further information on the pricing patterns over our data sample, we examine subsample estimates. These results are quite similar, and available in a web appendix, upon request from the authors.

[17]The data numbers used are those from Compustat.

preferred stock redemption value is not available, then preferred stock liquidation value (Data 10) is used. If neither redemption value nor liquidation value is available, then preferred stock par value (Data 130) is used.

Book value of liabilities: Long-term debt (Data 9) + debt in current liabilities (Data 34) is used in all tables except 7. Following methodology established earlier, total liabilities (Data 181) is used for Table 7. If the value of total liabilities is not reported, then total assets (Data 6) − book value of equity as computed above is used.

Current assets: Data 4 is used.

Current liabilities: Data 5 is used.

EBIT: Pretax income (Data 170) + interest expense (Data 15) is used.

Funds from operations: When available, Data 110 is used. If not reported, operating income before depreciation (Data 13) is used.

Leverage or D/E = Book value of debt. This is divided by the market value of equity. The amount of total liabilities (Data 181) is used as book value of debt. If the value of total liabilities is not reported, then total assets (Data 6) − book value of equity as computed above is used. Market value of equity is obtained by multiplying the number of shares outstanding with the price from the last trading day from CRSP.

Net income: Data 172 is used.

Retained earnings: Data 36 is used.

Sales: Data 12 is used.

Total assets: Data 6 is used.

Working capital: Data 179 is used.

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