The Bright Side of Distress Risk

Alexander Barinov

School of Business
University of California Riverside

E-mail: **abarinov@ucr.edu**
http://faculty.ucr.edu/~abarinov

Abstract

The paper shows that distressed firms earn positive abnormal returns when aggregate volatility unexpectedly increases. This hedging property of distressed firms explains the puzzling negative relation between firm-specific distress risk and future alphas from benchmark asset-pricing models. Controlling for aggregate volatility risk exposure also explains why the negative relation is stronger for volatile firms and growth firms.

JEL Classification: G11, G12, G14, E44

Keywords: distress, default, aggregate volatility risk, credit ratings, idiosyncratic volatility, anomalies

1 Introduction

The contradictory evidence on pricing of distress risk for common stocks has long been puzzling to the asset-pricing literature. On the one hand, the default spread (commonly defined as the yield differential between Aaa and Baa bonds) is widely recognized as an important state variable. Fama and French (1989) find that high default spread signals recessions and predicts higher expected market return going forward. Petkova and Zhang (2005) and Akbas et al. (2010) successfully use default spread in the conditional CAPM and the conditional liquidity CAPM and conclude that higher risk in the periods of high default spread leads to higher expected returns. Fama and French (1993), Eckbo et al. (2000), Hahn and Lee (2006), and Petkova (2006) successfully use default spread as an asset-pricing factor and find that it contributes to explaining the value effect and the SEO underperformance.

On the other hand, sorting stocks on various measures of distress risk reveals that stocks that should have the highest distress risk have lower, not higher risk-adjusted returns. Dichev (1998) finds that firms with higher O-score and lower Z-score[1] have significantly lower future alphas. Avramov et al. (2009a) find the same for firms with bad credit rating, and Campbell et al. (2008) find similar evidence using their own default-predicting regression. This collective evidence is henceforth referred to as the distress risk puzzle.

The negative relation between default probability and expected returns seems so obviously backward that the prevalent explanations of it assume it is mispricing. Griffin and Lemmon (2002) hypothesize that the negative relation between O-score/Z-score and size-adjusted returns arises because investors fail to acknowledge the grim future of distressed growth stocks. Avramov et al. (2009a) attribute the negative relation between credit rating and expected returns to the investors' failure to fully acknowledge potentially devastating effects of future downgrades.

Several papers attempt to offer a rational explanation of the distress risk puzzle by suggesting that risk of distressed firms is mismeasured by existing asset pricing models.

[1] O-score is constructed by Ohlson (1980) and estimates expected probability of default. Z-score is created by Altman (1968) and is a measure of financial health. Both O-score and Z-score use publicly available accounting data.

Garlappi et al. (2008) argue that traditional risk measures (e.g., Fama-French betas) can overstate the true risk of distressed firms' equity if shareholders have large bargaining power and are able to push most of the firm's risk on debtholders in the event of default. George and Hwang (2010) hypothesize that firms that suffer the most in the event of default and therefore have the highest default risk select to have low leverage and low probability of default, which means that sorting on default probability will create an inverse sort on default risk.

What is missing from the risk-based explanations of the distress risk puzzle is the ultimate evidence that if one measures risk of distressed firms correctly, their alphas are gone. This paper aims to fill this void by showing that the alphas disappear once one controls for aggregate volatility risk, thus also identifying the state variable, the exposure to which makes distressed firms less risky than commonly thought. Though my explanation of why distress risk is negatively related, in cross-section, to aggregate volatility risk exposure, is different from the ones in Garlappi et al. (2008) and George and Hwang (2010), it is not mutually exclusive with respect to any of them and the mechanisms described in Garlappi et al. (2008) and George and Hwang (2010) might also generate the negative cross-sectional relation between firm-specific distress risk and aggregate volatility risk exposure.

My explanation of the distress risk puzzle is based on the argument that extends the model in Johnson (2004). Johnson (2004) looks at equity as a call option on the firm's assets and shows that if uncertainty about the firm's assets increases, the elasticity of the call option's value with respect to the value of the underlying asset decreases and the beta of equity therefore decreases. The intuition is that more uncertainty about the underlying asset (firm's assets) means that its current value is less informative about the value of the option (firm's equity) at the expiration date. Therefore, the current value of the option responds less to the same percentage change in the current value of the underlying asset if there is more uncertainty about the underlying asset's true value.

Johnson (2004) also notices that the effect of firm-specific uncertainty on the firm's expected returns should be stronger for highly levered firms. The intuition is that uncertainty derives its pricing impact from the fact that a levered firm is a call option on the assets, and therefore volatility should matter more for highly levered firms.

Higher leverage in the Johnson model makes equity more risky by levering up its beta, but the caveat is that it is a partial derivative effect. The empirical correlation between distress and expected returns that ignores the distress-uncertainty interaction can become negative in the data if the interaction effect is large enough and if highly levered firms are significantly more volatile than healthy firms. Hence, the Johnson model predicts that highly levered firms with high uncertainty have low expected returns, potentially even lower than expected returns of low leverage firms with low to medium uncertainty.[2]

While the Johnson model explains how some distressed firms can have lower systematic risk than healthy firms, it does not explain why this lower systematic risk should show up as an alpha. If the CAPM and Johnson model are both true, distressed firms with high uncertainty should have low betas and zero alphas.

In this paper, I add the time series dimension to the Johnson argument. First, I rely on the evidence in Barinov (2013), Bartram et al. (2016), Duarte et al. (2012), and Herskovic et al. (2016) that, on average, idiosyncratic volatility and analyst disagreement increase in recessions together with market volatility. As the comparative statics exercise performed on the Johnson model in online Theory Appendix[3] shows, this increase lowers risk exposure of volatile levered firms and makes smaller the increase in their future discount rates and the consequent drop in price they witness during recessions.

Second, holding all else equal, the price of levered equity will receive a boost from an increase in total volatility, as the price of any option does. I conclude therefore that, holding everything else equal, the prices of distressed firms will decrease less than what the CAPM and other factor models predict when both aggregate volatility and uncertainty increase in recessions, as indicated by positive loadings of distressed firms on a volatility risk factor. The same comparative statics exercise in online Theory Appendix shows that positive elasticity of equity value with respect to uncertainty about assets value increases

[2]In the Johnson model, leverage is positively related to returns, holding everything else (i.e., firm-specific uncertainty) equal. However, single sorts on leverage can produce a negative relation between leverage and expected returns even in the Johnson world, if highly levered firms also have high uncertainty and low leverage firms have low uncertainty.

[3]Available at https://www.dropbox.com/s/kfq0ernp1kousps/Theory blind.pdf?dl=0

with leverage and is particularly high for volatile levered firms.[4]

I do not argue that simply buying distressed firms can offer a protection against recessions. Their equity is a highly levered claim on assets, and therefore their betas are likely to be high. Also, distressed firms will be vulnerable to recessions because of other reasons, such as lack of free cash and inability to borrow. What I argue is that distressed firms will suffer in recessions significantly less than what their market betas imply, because the CAPM (as well as other factor models) misses the positive effects of higher volatility on equity of distressed firms. This is the reason why alphas of distressed firms come out to be negative in the existing asset pricing models. Distressed firms can well be riskier than average. My point is that the existing asset pricing models paint them even riskier than that, and this is why their expected returns seem too low.[5]

A good example can be the performance of firms in the bottom credit rating quintile (B+ and below on the S&P scale) in 2008-2009, when average realized return to both those firms and the market portfolio was -70 bp per month. In the full sample though, the market beta of the bottom credit rating quintile is 1.69, which means that this quintile portfolio should have lost 1.69 times what the market lost. The positive difference between the CAPM forecast and the realized returns to distressed firms (roughly $(1.69 \cdot 70 - 70 = 50$ bp per month) during the most recent recession represents the hedging power of distressed firms against volatility increases.

Abnormally good performance during aggregate volatility increases is a desirable thing. Campbell (1993) creates a model, in which increasing aggregate volatility is synonymous with decreasing expected future consumption. Investors would require a lower risk premium from stocks the value of which correlates positively with aggregate volatility news, because these stocks provide additional consumption precisely when investors have to cut their current consumption for consumption-smoothing motives. Chen (2002) adds the

[4]The second channel is similar to the result from options literature that the option's vega (option value derivative with respect to volatility) is the largest when the option is at the money. My analysis looks at elasticity of equity value with respect to uncertainty (vega times the uncertainty parameter divided by the option value). Simulations show that the elasticity increases with uncertainty and leverage for a broader range of parameters. A more thorough discussion is in online Theory Appendix.

[5]Another way to put it is that the market-neutral position in distressed firms (buy distressed firms, short the market to cancel out their CAPM beta) is a hedge against recessions/volatility increases.

precautionary savings motive and concludes that positive correlation of asset returns with aggregate volatility changes is desirable, because such assets deliver additional consumption when investors have to consume less in order to boost precautionary savings in the face of a persistent positive shock to volatility. Ang et al. (2006) confirm these predictions empirically and coin the notion of aggregate volatility risk. They show that stocks with the most positive sensitivity to aggregate volatility increases have abnormally low expected returns and that the portfolio tracking expected aggregate volatility earns a significantly negative risk premium.

My paper builds on this literature and shows that distressed firms have negative CAPM alphas because they load negatively on aggregate volatility risk. The main contribution of the paper is the use of aggregate volatility risk to explain a prominent anomaly; I do not argue that the two-factor ICAPM with the market factor and FVIX (or any other model augmented with FVIX) is a superior asset pricing model that on average prices all anomalies better than other models.

The main part of the empirical analysis uses the volatility risk factor I call FVIX. The FVIX factor is a factor-mimicking portfolio that tracks daily changes in the VIX index. I use the old definition of the VIX index (current ticker VXO) to obtain longer coverage. The old VIX index is implied volatility of options on the S&P 100 index and therefore measures expected aggregate volatility. As Ang et al. (2006) show, at daily frequency VIX is highly autocorrelated, and thus its change is a good proxy for innovation in expected aggregate volatility. Ang et al. (2006) also show that FVIX factor is priced.

My explanation of the distress risk puzzle also produces several cross-sectional implications. First, similar to the Johnson model, I predict that distressed firms with high uncertainty measures have the most positive FVIX betas. The empirical predictions are two-fold: I expect that the distress risk puzzle is stronger for high uncertainty firms and I expect that my volatility risk factor would explain this pattern. The first prediction was already tested in Chen et al. (2010) for O-score and Z-score and in Avramov et al. (2009b) for credit risk, and my contribution is that this relation has a rational explanation – volatility risk.

Second, I expect that the negative relation between distress and volatility risk will be stronger for growth firms. My reasoning is that leverage makes equity a call option on the assets, and this option-likeness of equity makes it load negatively on volatility risk. If the assets are themselves growth options, the option-likeness is even stronger, and therefore distressed growth firms will load most negatively on volatility risk and have the most negative CAPM alphas. Hence, I provide a rational explanation of the evidence in Griffin and Lemmon (2002) that distressed growth firms have the most negative CAPM alphas and that the distress risk puzzle is the strongest for growth firms. I also indirectly contribute to the value effect literature, because the flip side of the evidence that the distress risk puzzle is stronger for growth firms is that the value effect is stronger for distressed firms, and I find that volatility risk can also explain that.

The rest of the paper proceeds as follows. Section 2 provides a brief literature review, and Section 3 discusses the data sources, while Section 4 performs preliminary tests. Section 5 presents evidence that volatility risk explains the distress risk puzzle. Section 6 looks at the relation between the distress risk puzzle and firm-specific uncertainty, market-to-book, and leverage and shows that aggregate volatility risk explains the cross-section of the distress risk puzzle. Section 7 summarizes robustness tests that are discussed in more detail in an online Robustness Appendix.[6]

2 Literature Review

Campbell et al. (2008) provide the first brief analysis of whether aggregate volatility risk can explain the distress risk puzzle. They dismiss this possibility based on the fact that returns to the healthy-minus-distressed strategy have a positive correlation with the change in VIX, which suggests that the strategy wins when VIX goes up and therefore is not risky. The evidence in this paper shows that such conclusion is premature: the healthy-minus-distressed strategy also has a strongly negative market beta (-0.82 in value-weighted and -0.53 in equal-weighted returns) and thus it is supposed to gain in bad times, when VIX

[6]Available at https://www.dropbox.com/s/6rb5o3t9abxiv52/Robustness blind.pdf?dl=0.

increases.[7] The point this paper is making is that this strategy does not gain nearly as much as the CAPM (or other asset pricing models) predicts in periods of increasing market volatility, and hence the CAPM/other models underestimate its risk and expected returns and produce positive alphas.[8]

Two empirical papers related to my paper are O'Doherty (2012) and Eisdorfer and Misirli (2020). O'Doherty (2012) uses an argument based on Johnson (2004) to argue that market betas of distressed firms should be procyclical and finds that Conditional CAPM (CCAPM) reduces the distress risk puzzle to statistically insignificant values of roughly 35 bp per month.[9] In this paper, I suggest that a second factor, FVIX, is needed to explain the distress risk puzzle, and propose an additional, simpler and stronger, channel that implies relatively good performance of distressed companies during recessions: their equity is a call option on the assets, and higher volatility increases the equity value holding everything else fixed. The focus on expected market volatility as a state variable is also new compared to O'Doherty (2012). Empirically, I find in Table 2 and in Section 7.4 that FVIX is significantly more successful in explaining the distress risk puzzle and FVIX largely subsumes the effect of conditional market beta.

Eisdorfer and Misirli (2020) find that the healthy-minus-distressed strategy works only in bull markets, but breaks down in bear markets. This evidence is consistent with the evidence in the paper that distressed firms do abnormally well when expected market

[7]The standard way of finding out whether the healthy-minus-distressed strategy is negatively exposed to VIX changes controlling for the market beta is the multiple regression of returns to the strategy on the market and FVIX, which is what Table 2 performs, finding a significant FVIX exposure of the strategy (FVIX beta) once the market factor is controlled for. Another way to control for the market factor would be to look at partial correlations (conditional on market return) between returns to credit rating quintiles and FVIX: in untabulated results, I find that they increase from -0.47 for the best credit rating quintile to 0.38 for the worst credit rating quintile. Yet another way is to look at firm-level CAPM alphas and their correlation with change in VIX, which ranges from -0.26 for healthy firms to 0.2 for distressed firms.

[8]Again, 2008-2009 can be a good example here: the cumulative return to the healthy-minus-distressed portfolio was -10.8%, while the cumulative return to the market portfolio was -20.1%. As a negative-beta asset, the healthy-minus-distressed portfolio should have had strongly positive, not negative return, when the market goes down by 20%. Further analysis suggests that this unexpected performance was driven primarily by positive abnormal returns to distressed firms.

[9]In Table 3 (5) in O'Doherty (2012), the distress risk puzzle in the CCAPM is estimated to be between 35 bp and 64 bp (28 bp and 50 bp) per month, Panel B of Table 2 in O'Doherty (2012) gives more moderate ranges of 17 bp to 38 bp per month and -16 bp to 20 bp per month. In my setup, Panel C of Table pegs the distress risk puzzle in the CCAPM at 53 bp to 68 bp per month.

volatility (VIX) increases.

A recent theory paper by McQuade (2018) develops an intuition similar to my explanation of the distress risk puzzle in a real-options model with stochastic volatility and endogenous default. In the model, distressed firms serve as hedges against volatility risk, since the value of their option to default, just like the value of any option, increases in volatility all else fixed. The McQuade model does not look at the second channel I consider, which suggests that distressed firms' betas decline when volatility increases (and thus their expected return increases less and their value drops less in recessions).

One can view my paper as an empirical test of the mechanism in the purely theoretical work of McQuade (2018). Alternatively, one can also say that my explanation of the distress risk puzzle and McQuade (2018) focus on different components of volatility. The model in McQuade (2018) is solved using asymptotic expansions, so if one takes the model literally, it seems to say that distressed firms offer a hedge against the long-run component of market volatility. The state variable in my paper is VIX, which is the implied volatility of one-month options on the market and thus sounds more like short-run volatility.

In Section 7.5, I split volatility into those two components using Component GARCH as in Adrian and Rosenberg (2008), and find that FVIX overlaps with short-run market volatility, but long-run market volatility seems to be helping healthy rather than distressed firms. This evidence also suggests that FVIX is not related to the recent long-run volatility factor of Campbell et al. (2018), which is unlikely to contribute to the explanation of the distress risk puzzle.

I find in my previous work (Barinov and Chabakauri, 2019, Barinov, 2012, 2013, 2018) that FVIX can explain multiple puzzles, such as the new issues puzzle, the cumulative issuance puzzle of Daniel and Titman (2006), the negative relation between expected returns and analyst disagreement (from Diether et al., 2002), the negative relation between idiosyncratic volatility and expected returns (from Ang et al., 2006), and the maximum effect of Bali et al. (2011). While the economic mechanism in the current paper and in the prior papers is similar (option-like volatile equity is a hedge against volatility risk), the current paper focuses on the option-likeness created by leverage, while the other papers look at growth options. In the data, leverage and growth options are negatively related, so the evidence in the previous work that volatile growth firms load positively on FVIX works against me finding in this paper the link between (volatile) distressed firms and aggregate volatility risk. I also find in Section 5 of the online Robustness Appendix that the overlap between the distress risk puzzle and the anomalies above is within 30%, and credit rating remains significant in cross-sectional regressions after controlling for idiosyncratic volatility, analyst disagreement, or maximum daily return in the past month, while controlling for FVIX explains 50-100% of the distress risk puzzle and makes the rest statistically insignificant.

3 Data

The main distress measure used in the paper is credit rating (from S&P, reported monthly in the Compustat adsprate file). Two more alternative measures are Ohlson (1980) O-score, and the "naïve" version of expected default frequency (EDF) proposed by Bharath and Shumway (2008), who find that the "naïve" EDF is an even better predictor of bankruptcy than EDF from a full-blown solution of the Merton (1974) model. O-score and EDF are computed annually using data from Compustat annual file. The detailed description of O-score and EDF is in online Data Appendix,[10] which also holds the definition of all other variables used in the paper.

The portfolio sorts in the paper use NYSE (exchcd=1) breakpoints. Financial firms and stocks with prices below $5 on the portfolio formation date are excluded. As Section 10 in online Robustness Appendix shows, the results in the paper are robust to using CRSP breakpoints and/or including the stocks priced below $5 back into the sample.

To measure the innovations to expected aggregate volatility, I use daily changes in the old version of the VIX index calculated by CBOE and available from WRDS. Using the old version of VIX (current ticker VXO) provides longer coverage. The VIX index measures the implied volatility of the at-the-money options on the S&P100 index.

I form a factor-mimicking portfolio that tracks the daily changes in the VIX index. I

[10] Available at https://www.dropbox.com/s/sgo64j5x4k17np6/Data Appendix.pdf?dl=0.

regress the daily changes in VIX on the daily excess returns to the base assets.[11] The base assets are five quintile portfolios sorted on the past return sensitivity to VIX changes, as in Ang et al. (2006):

$$\Delta VIX_t = \underset{(0.019)}{0.060} - \underset{(0.074)}{0.052} \cdot (VIX1_t - RF_t) - \underset{(0.156)}{0.611} \cdot (VIX2_t - RF_t) - \underset{(0.113)}{0.376} \cdot (VIX3_t - RF_t)$$
$$- \underset{(0.386)}{0.679} \cdot (VIX4_t - RF_t) + \underset{(0.143)}{0.194} \cdot (VIX5_t - RF_t), \quad R^2 = 0.474 \tag{1}$$

where $VIX1_t, \ldots, VIX5_t$ are the VIX sensitivity quintiles described below, with $VIX1_t$ being the quintile with the most negative sensitivity. The fitted part of the regression above less the constant is my aggregate volatility risk factor (FVIX factor).[12]

The return sensitivity to VIX changes ($\gamma_{\Delta VIX}$) I use to form the base assets is measured separately for each firm-month by regressing daily stock excess returns in the past month on daily market excess returns and the VIX index change using daily data (at least 15 non-missing returns are required):

$$Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \gamma_{\Delta VIX} \cdot \Delta VIX_t. \tag{2}$$

In untabulated results, I find that the results in the paper are robust to changing the base assets from the VIX sensitivity quintiles to ten industry portfolios from Fama and French (1997) or six size and book-to-market portfolios from Fama and French (1993).

The sample in the paper starts in January 1986 (due to availability of VIX index) and ends in December 2016 (due to availability of Compustat data on credit rating).

[11] The factor-mimicking regression is performed using the full sample to increase the precision of the estimates. In Section 7.6, I find that all results in the paper are robust to using an out-of-sample version of FVIX that is estimated using expanding window. I decide against using the out-of-sample version of FVIX as the main specification, since the learning sample has to include at least three years to make the estimates stable, and that implies that the VIX spike of October 1987 will be left out of the sample in asset-pricing tests.

[12] FVIX is a zero-investment portfolio that uses the slopes from the factor-mimicking regression as weights: shorting VIX1 quintile for \$52 (and buying Treasuries for \$52), then shorting VIX2 quintile for \$611 (and buying Treasuries for \$611), etc. creates FVIX.

4 Preliminary Tests

4.1 Descriptive Statistics

Table 1 performs quintile sorts on credit rating and reports median firm characteristics for each quintile. I choose credit rating as the main variable of my analysis, since Avramov et al. (2009a) show that sorting on credit rating creates larger spread in expected returns than sorting on other distress measures. Another advantage of credit rating is that while all other distress measures measure probability of default, credit rating also considers recovery rate and thus comes closer to estimating expected losses from default.[13]

Panel A of Table 1 looks at alternative distress measures across credit rating quintiles and finds that sorting on credit rating creates a strong spread in all other distress measures as well. For example, median leverage more than triples, and expected default frequency (EDF) increases roughly by a factor of 50 as one goes from the quintile with the best to the quintile with the worst credit rating. Thus, all results I document using credit rating are also likely to go through using other distress measures (Section 1 of online Robustness Appendix[14] provides further evidence on that).

Panel B looks at various measures of firm-specific uncertainty across credit rating quintiles. My explanation of the distress risk puzzle suggests that distressed firms are hedges against increases in aggregate volatility if they are also volatile. In the Johnson model that derives a negative relation between expected returns and the distress-volatility interaction, but produces a positive relation between distress and expected returns holding firm-specific volatility fixed, higher volatility of distressed firms is a necessary condition for distress being negatively associated with expected returns in single sorts.

In Panel B of Table 1, I find that as one goes from firms with the best to firms with the worst credit rating, idiosyncratic volatility of returns doubles, variability of earnings and cash flows quadruples, and analyst disagreement and analyst forecast error increase

[13] Expected losses from default equal probability of default times expected loss in the event of default. Credit rating depends on the expected losses of bondholders, not shareholders, but the two are likely to be closely correlated - unless an extreme case of risk transfer from equityholders to debtholders happens during bankruptcy, as Garlappi et al. (2008) suggest is the case for some firms.

[14] Robustness Appendix is available at https://www.dropbox.com/s/6rb5o3t9abxiv52/Robustness blind.pdf?dl=0.

by a factor of five. Thus, firms with bad credit rating are exactly of the type that would be the best hedges against aggregate volatility risk: they are not only option-like, but also have high firm-specific volatility. In online Robustness Appendix, I also show that distressed firms are still more volatile even after their higher leverage is controlled for - in other words, not only their equity, but also their assets have higher volatility.

Panel C looks at two additional measures of option-likeness, suggested in Grullon et al. (2012). These measures estimate convexity in the firm value by looking at its response to large shocks. In particular, "SUE flex" measure is the slope on the squared earnings surprise in the regression of earnings announcement returns on earnings surprise and its square, and "TVol sens" measure is the slope from the regression of monthly firm return on market return and change in total firm volatility. Hence, "SUE flex" measures the asymmetric response to large good and large bad news (which is the essence of convexity in distressed firms brought about by limited liability), and "TVol sens" looks exactly at the positive effect of increases in total firm volatility on firm value that is the focus of my explanation of the distress risk puzzle.

Panel C shows that both convexity measures increase dramatically as one moves from firms with the best to firms with the worst credit rating. Firms with bad credit rating indeed respond asymmetrically stronger to big positive news, underscoring the importance of convexity in their value. The value of distressed firms also responds much more positively to the firm becoming more volatile, which is the direct evidence of the main mechanism in the paper being at work.

4.2 Sensitivity of Firm-Level Volatility to Economy-Wide Volatility

Panel D of Table 1 tests the hypothesis that firm-specific volatility of distressed firms (which are also high uncertainty firms, as Panel B shows) is more responsive to changes in market-wide volatility. My explanation of the distress risk puzzle suggests that volatile distressed firms witness a smaller drop in value and a smaller increase in risk when their idiosyncratic volatility increases by a given percentage. Unless idiosyncratic volatility of volatile distressed firms reacts less to VIX changes than idiosyncratic volatility of healthy firms, my explanation of the distress risk puzzle implies that volatile distressed firms are less exposed to volatility risk and their market betas are more procyclical.

In the first row of Panel D, I regress changes in idiosyncratic volatility of individual firms on changes in VIX and report the average slopes in each credit rating quintile. The slopes increase monotonically and in the end more than double going from best to worst credit rating quintile, confirming my hypothesis that volatility of distressed companies is more responsive to economy-wide changes in volatility, both systematic and idiosyncratic.

The second row of Panel D repeats the first row using percentage changes in both left-hand side and right-hand side variables and finds that the percentage response of idiosyncratic volatility to VIX changes is flat across credit rating quintiles. In other words, the first row finds that volatility of distressed firms is more responsive to VIX changes only because distressed firms are more volatile and thus large volatility changes for them are more likely.

The third and fourth row repeat rows one and two using analyst disagreement instead of idiosyncratic volatility and find an even stronger relation between credit rating and responsiveness of firm-level analyst disagreement to changes in VIX - the slope increases ten-fold and six-fold, respectively, from best to worst credit rating quintile.[15]

It is also worth noting that all slopes in all quintiles in Panel D are significantly positive, consistent with previous evidence in Barinov (2013), Bartram et al. (2016), Duarte et al. (2012), and Herskovic et al. (2016) that average idiosyncratic volatility is significantly correlated with market volatility, and both tend to increase during recessions. Section 8 in online Robustness Appendix presents further evidence on that.

[15]Barinov (2017) also performs sorts on idiosyncratic volatility and analyst disagreement and shows that similar evidence arises, confirming the direct link between the level of firm-specific uncertainty and its sensitivity to economy-wide changes in uncertainty/volatility.

5 Distress Risk Puzzle and Aggregate Volatility Risk

5.1 FVIX as an Aggregate Volatility Risk Factor

The main prediction of this paper is that the distress risk puzzle is explained by aggregate volatility risk, i.e., by the fact that firms with bad credit rating tend to perform relatively well in response to unexpected increases in aggregate volatility.

In the tests of this hypothesis, I use the FVIX factor, the aggregate volatility risk factor that has been shown to be priced in a broad cross-section (see Ang, Hodrick, Xing, and Zhang, 2006, and Barinov, 2012) and has been shown to explain several important anomalies, including the idiosyncratic volatility discount of Ang et al. (2006) (see Barinov and Chabakauri, 2019), the analyst disagreement effect of Diether, Malloy, and Scherbina (2002) (see Barinov, 2013), and the new issues puzzle (see Barinov, 2012).

FVIX is the factor-mimicking portfolio that mimics daily innovations to the VIX index (see Section 3 and online Data Appendix for the discussion of the factor-mimicking procedure). FVIX represents the combination of zero-investment portfolios (the base assets) that has the highest positive correlation with the VIX change (my proxy for innovations to VIX).

In order to be a valid and useful ICAPM factor, FVIX factor has to satisfy three requirements. First, it has to be significantly correlated with the variable it mimics (the change in VIX). In Section 3, I find that the R-square of the factor-mimicking regression is 0.474, and the correlation between FVIX returns and VIX changes is then expectedly high at 0.69. I conclude that FVIX clears the first hurdle of being a good mimicking portfolio.

Second, FVIX has to earn sizeable and statistically significant risk premium, both in raw returns and, most importantly, on the risk-adjusted basis. Since FVIX is, by construction, positively correlated with VIX changes, FVIX represents an insurance against increases in aggregate volatility, and, as such, has to earn a negative risk premium. Untabulated results show that the average raw return to FVIX is -1.37 per month, t-statistic -4.77, and the CAPM alpha and the Fama-French alpha of FVIX are both at about -44 bp per month, t-statistics -4.00 and -3.91, respectively. I conclude that FVIX captures important risk investors care about, because the negative alphas suggest they are willing to pay a significant amount for the insurance against this risk provided by FVIX. Hence, FVIX clears the second hurdle for being a valid ICAPM factor.

Third, as Chen (2002) suggests, a valid volatility risk factor should be able to predict future volatility. Barinov (2013, 2018) shows that FVIX returns indeed predict several measures of expected and realized market volatility. Thus, FVIX clears the third and final hurdle for being a valid volatility risk factor.

5.2 Explaining the Distress Risk Puzzle

Table 2 performs quintile sorts on credit rating and reports the alphas and FVIX betas from several factor models before and after augmenting them with the FVIX factor. The credit rating portfolios are rebalanced each month; I also skip a month between portfolio formation and return calculation to eliminate any microstructure effects or any delayed effects of credit rating downgrades.[16] The top row of each panel reports average credit rating of firms in each credit rating quintile.

The top two panels use the CAPM as the benchmark model and estimate the distress risk puzzle (defined as the alpha differential between the best and worst credit rating quintiles) at 83 bp (80 bp) per month in value-weighted (equal-weighted) returns. Value-weighted alphas present the familiar evidence (similar to Avramov et al., 2009a) that the distress risk puzzle is driven primarily by the worst credit rating quintile. Equal-weighted alphas are uniformly more positive due to the strong size effect in equal-weighted returns and suggest that the distress risk puzzle comes equally from the long and short sides.

Most importantly, the top two panels of Table 2 (A1 and B1) reveal that the two-factor ICAPM with the market factor and FVIX can explain alphas of all credit rating quintiles and reduce the healthy-minus-distressed alpha differential to insignificantly negative values. The driving force is FVIX betas, which are significantly positive for distressed firms (indicating abnormally good performance when aggregate volatility increases) and significantly negative for healthy, less option-like firms. The increase of FVIX betas across credit

[16]The results in the paper are robust to not skipping a month.

rating quintiles is also strongly monotonic and significant.

The next two panels (A2 and B2) use the Carhart (1997) model as the benchmark. Controlling for the fact that distress firms are likely to be recent losers, and healthy firms are somewhat likely to be recent winners seems to explain a significant fraction of the distress risk puzzle. The Carhart model estimates the distress risk puzzle at 44-61 bp per month, still economically significant (and statistically significant in the case of equal-weighted returns).[17] Yet, the explanatory power of FVIX and the FVIX beta spread between healthy and distressed firms remain large and significant in the Carhart model: after I control for FVIX, alphas of the worst credit rating quintile are within 7 bp of zero, their differences with alphas of the best credit rating quintile are within 4 bp of zero, and the FVIX beta differential between healthy and distressed firms has t-statistics exceeding 3.3.[18]

To sum up, Panels A1-A2 and B1-B2 of Table 2 presents the main result of the paper that the FVIX factor can explain the distress risk puzzle and that distressed firms are hedges against aggregate volatility risk. The result is remarkably robust to alternative benchmark models. In untabulated results, I have also tried adding the Pastor and Stambaugh (2003) liquidity factor and/or a factor based on the Jegadeesh (1990) short-term reversal to the Carhart model and arrived at very similar results.[19]

I also find in untabulated results that the distress risk puzzle has a significant overlap with the new profitability (RMW) factor from the five-factor version of the Fama-French

[17]In untabulated analysis, I bootstrap the standard errors in Panel B and find that the lack of significance for value-weighted Carhart alphas is largely a power issue: with 5000 redraws, the significance of the worst credit rating quintile alpha is restored at 10% level and the significance of the B-W alpha is restored at 5% level even with 1000 redraws. Bootstrapping has little effect on the t-statistics of alphas from the Carhart model augmented with FVIX (Carhart+V model in the table) and further improves the significance of FVIX betas.

[18]In untabulated results, I try sorting firms into credit rating deciles, which produced a larger and more significant spread in CAPM/Carhart alphas, but did not impact the ability of FVIX to explain the said alpha spread.

[19]In Section 10 of online Robustness Appendix, I have experimented with including stocks priced below $5 back into the sample, since dropping low-price stocks can potentially weaken the distress risk puzzle. I found that in equal-weighted returns, the distress risk puzzle is a bit stronger with stocks priced below $5 included - for example, the CAPM alpha of the healthy-minus-distressed portfolio changes from 80 to 84 bp per month. The FVIX beta of that portfolio changes accordingly though, and the ICAPM alpha changes from 16 bp in Panel A of Table 2 to -6 bp in untabulated results with stocks priced below $5 included.

model. The five-factor model generates a smaller healthy-minus-distressed alpha than the Carhart model, though the spread in CMA betas between healthy and distressed firms is not always significant. Further analysis reveals that FVIX explains the alpha of RMW, but RMW cannot explain the alpha of FVIX, suggesting that volatility can be the state variable behind RMW (Barinov, 2022, presents detailed analysis of this hypothesis). Adding FVIX to the five-factor Fama-French model reduces the spread in both RMW and FVIX betas between healthy and distressed firms, but leaves both beta spreads significant.

5.3 Distress Risk Puzzle in the Conditional CAPM

Panels A3 and B3 of Table 2 demonstrate the existence of the first channel that links the distress risk puzzle and aggregate volatility risk. The first channel predicts procyclical market betas of distressed firms. The first row of Panels A3 and B3 tabulates Conditional CAPM alphas from the standard version of the Conditional CAPM with four conditioning variables: default premium, dividend yield, Treasury bill yield, and term spread. In value-weighted returns, I observe that the alpha of the healthy-minus distressed strategy (B-W column) declines by 30 bp per month (from 83 to 53 bp per month) after the market beta is made time-varying, and the decline is coming primarily from the fact that the alpha of distressed firms is smaller in the Conditional CAPM, consistent with the prediction of the first channel that their beta is more procyclical. In equal-weighted returns, the decrease in the alphas is more modest; overall, the evidence is consistent with the one presented by O'Doherty (2012): the Conditional CAPM contributes to explaining the distress risk puzzle, but leaves a large fraction of it unexplained.

The next three rows of Panels A3 and B3 tabulate conditional betas of credit rating quintiles in recessions (row two) and expansions (row three), as well as the difference in the betas recessions vs. expansions (row four).[20] In value-weighted returns, I observe a large

[20]The definition of expansion and recession in Panels A3 and B3 follows the tradition in the Conditional CAPM literature (see., e.g., Petkova and Zhang, 2006): recession is defined as a period of high expected market risk premium (signifying high risk of investing in the market and high marginal utility of consumption). Empirically, I use the four commonly used conditioning variables for the market beta (DIV, DEF, TB, TERM) to forecast the market risk premium and define recessions as periods with forecasted market risk premium above in-sample median. Making the market beta a function of the same variables that predict the market risk premium is necessitated by the fact that the alpha differential be-

shift in the conditional beta of healthy-minus distressed strategy, which increases by 0.56 during recessions – mostly because the conditional beta of the worst credit rating quintile decreases in recessions by 0.47, strongly supporting the prediction that market betas of volatile distressed firms are procyclical. The difference in betas between expansions and recessions in the other credit rating quintiles is small and is largely flat across the quintiles, because firms in these quintiles are not option-like enough and their equity is deeply in the money (see Panel C of Table 1 for the evidence that option-likeness increases sharply in the worst credit rating quintiles, and in the other quintiles it largely stays flat).

In equal-weighted returns, Conditional CAPM betas are uniformly higher during recessions for all credit rating quintiles but the worst one, where the recessions vs. expansion difference in market betas takes a sharp and statistically significant dip, consistent with my prediction. The predominance of positive differences in the other quintiles reflects the fact that small firms that dominate equal-weighted returns are more sensitive to the business cycle and become riskier in bad times; this predominance also explains why the recessions vs. expansion difference in market betas for the worst credit rating quintile is zero rather than positive in equal-weighted returns.

5.4 Distress Risk Puzzle in Cross-Sectional Regressions

Table 3 tests the robustness of the main result of the paper by using cross-sectional regressions instead of portfolio sorts. I use the technique described in Brennan et al. (1998) and control for known risk factors by performing risk-adjustment to the left-hand side variable. That is, in the first column of Table 3 the dependent variable is raw return, in the second column the dependent variable is abnormal return from the CAPM, in the third column the dependent variable is abnormal return from the two-factor ICAPM with the market and FVIX, etc. The calculation of abnormal return starts with estimating the factor betas for each firm-month, using firm-level returns in months t-1 to t-36. The abnormal return in month t is the raw return less the sum of the products of these betas

---

tween the CAPM and Conditional CAPM equals the covariance between conditional beta and expected market risk premium, i.e., if a variable is driving only one of them, this variable does not contribute to the covariance/alpha differential and can be omitted from the analysis. For a more detailed discussion, see p. 217–218 in Barinov et al. (2020).

with factor returns in month t.[21] My hypothesis is that my main variable, credit rating, will be significant in all regressions, in which the risk-adjustment does not include FVIX, and will lose significance once the risk-adjustment includes FVIX.

Columns one, two, four, and six of Table 3 confirm the result in Table 2 that the distress risk puzzle is equally strong and significant in CAPM, Fama-French, and Carhart alphas, and weaker, though still large and significant at the 10% level, in raw returns. In terms of the economic magnitude, the slope on the credit rating reports the reaction of expected return, in basis points, to one grade change in credit rating.[22] Thus, the second column shows, for example, that the change in credit rating between the best and worst quintiles (nine grades, from A+ to B+) should imply the CAPM alpha spread of 65 bp per month, which is close to the spread in CAPM alphas in Table 2.

Columns three, five, and seven of Table 3 confirm that controlling for aggregate volatility risk reduces the distress risk puzzle by at least one-half and leaves it insignificant at the 5% level. Similar to Table 2, adjusting for aggregate volatility risk has the biggest effect as one goes from the CAPM to ICAPM, because HML and FVIX overlap due to the ability of FVIX to partly explain the value effect (see Barinov and Chabakauri, 2019).

Table 3 also presents several additional interesting results. First, risk-adjustment generally works well, since market-to-book becomes insignificant once risk-adjustment includes Fama-French factors, and momentum is insignificant if risk-adjustment includes momentum factor. Second, comparing the CAPM and ICAPM column, one can observe that FVIX explains the value effect. Third, it is interesting that controlling for FVIX makes the slope on the momentum variable visibly smaller. This is somewhat at odds with Table 2, where I find little overlap between FVIX and the momentum factor, but may suggest that one reason why recent losers have low returns is that they become distressed and turn into hedges against aggregate volatility risk.

[21] In addition to different risk-adjustments on the left-hand side, all regressions in Table 3 include on the right-hand side the standard asset-pricing controls: size, market-to-book, cumulative return in months t-2 to t-12 (MOM), and return in month t-1 (REV). All right-hand side variables, except for credit rating, are rank variables that change between 0 and 1.

[22] The credit rating is coded as 1=AAA, 2=AA+, 3=AA, ... , 21=C, 22=D.

6 The Distress Risk Puzzle in Subsamples

6.1 Distress Risk Puzzle and Idiosyncratic Volatility

My explanation of the distress risk puzzle suggests that distressed firms, equity of which is similar to a call option on the assets, react in a more positive way to increases in firm-specific uncertainty. First, higher uncertainty about the assets means lower beta of equity. This effect comes handy in recessions, when both firm-specific uncertainty and aggregate volatility increase. Lower beta in recessions also implies smaller losses in recessions due to a muted increase in future discount rates. Second, higher firm-specific uncertainty implies higher values of equity as a call option on the assets, suggesting again that distressed firms have smaller losses in periods of high firm-specific and aggregate volatility than firms with comparable market betas.

As online Theory Appendix shows, both hedging channels above are likely to be stronger for distressed firms with high firm-specific uncertainty/volatility. As Panel D of Table 1 shows, for such firms firm-specific uncertainty is likely to change more if average level of firm-specific and aggregate volatility changes. Hence, the hedging power of distressed firms and therefore the distress risk puzzle should be stronger for high firm-specific uncertainty firms, and aggregate volatility risk should be able to explain this pattern.

Table 4 performs double sorts, first on idiosyncratic volatility and then on credit rating.[23] Panel A uses the CAPM as the benchmark model, Panel B repeats Panel A using the Carhart model instead of the CAPM.

Panels A1 and B1 confirm that, irrespective of risk-adjustment, the distress risk puzzle exists only in the subsample of high volatility firms. This is consistent with my explanation of the distress risk puzzle, as well as with evidence in Chen et al. (2010), who perform similar double sorts with O-score/Z-score instead of credit rating and find stronger distress risk puzzle for volatile firms, but favor a mispricing explanation.

Panels A2 and B2 look at the alphas of the double-sorted portfolios after FVIX is

[23]The sorts are conditional due to a strong correlation between idiosyncratic volatility and credit rating. In independent sorts, many firms fall on the "main diagonal", and the other corners, such as the portfolio of high volatility firms with the best credit rating, often have a single-digit number of firms (the mentioned portfolio has one or two firms in about 20 months in the early years of the sample).

added to the CAPM and Carhart model, respectively, and report two novel results. First, aggregate volatility risk is able to explain the distress risk puzzle in all analyst disagreement groups, as well as why the distress risk puzzle is stronger for high disagreement firms. Second, FVIX explains related evidence that the idiosyncratic volatility effect of Ang et al. (2006) is stronger for distressed firms (which is again consistent with my explanation of the distress risk puzzle).

Panels A3 and B3 look at FVIX betas in the double sorts and corroborate the evidence in Panels A2 and B2. Indeed, the FVIX beta of distressed firms is significantly more positive if these firms also have high idiosyncratic volatility. The large and positive FVIX beta of firms with bad credit rating and high idiosyncratic volatility is also responsible for significantly more negative FVIX betas of the healthy-minus-distressed strategy in the high volatility subsample and significantly more negative FVIX betas of the low-minus-high volatility strategy in the distressed firms subsample (both of these strategies short bad credit rating, high idiosyncratic volatility firms with their large and positive FVIX betas). Hence, FVIX betas in Panels A3 and B3 confirm that FVIX exposures explain why the distress risk puzzle is stronger for high volatility firms, just as my explanation of the distress risk puzzle would predict, and also why the idiosyncratic volatility effect is stronger for distressed firms, as follows from the same explanation.

Panel C of Table 4 tabulates average credit rating (coded as 1=AAA, 2=AA+, ... , 21=C, 22=D) in the double sorts and expectedly finds that higher volatility firms have worse credit rating – the difference in credit rating between low and high volatility groups is about 4 notches. However, the spread in credit rating between best and worst credit rating quintiles is the same in all three volatility groups, at about 9 notches - which is comparable to the spread in single sorts, reported in the rightmost column.

The rightmost column also suggests that the spread in credit rating in the low volatility group is similar to one-minus-four quintile spread from single sorts, while the similar spread in the high volatility group is close to two-minus-five quintile spread. Panel A1 of Table 2 estimates the respective alpha spreads at 64 bp and 55 bp per month, which suggests that the relation between idiosyncratic volatility and the distress risk puzzle documented in Table 4 is unlikely to be mechanical.

Panel D of Table 4 records the average number of firms in the double sorts.[24] In unconditional sorts, firms would be concentrated along the main diagonal, but conditional sorts in Table 4 spread out the firms rather well, making all portfolios balanced.[25]

In Section 2.1 of online Robustness Appendix, I redo Table 4 replacing idiosyncratic volatility with analyst disagreement, which limits my sample, but repeats the test in Avramov et al. (2009b). The results are similar to Table 4. The distress risk puzzle seems to be coming almost exclusively from high disagreement firms, and FVIX is able to explain the distress risk puzzle in this subsample. Symmetrically, the analyst disagreement effect of Diether et al. (2002) comes from the quintile of firms with the worst credit rating, as Avramov et al. (2009b) find – and I add to that the new evidence that FVIX can explain this pattern.

Section 9.2 of online Robustness Appendix presents a more direct test of my prediction about conditional market betas of the healthy-minus-distressed strategy during recessions and expansions in the high and low idiosyncratic volatility/analyst disagreement subsamples. I find that in high volatility/disagreement subsample the healthy-minus-distressed strategy is riskier, because its beta is significantly more countercyclical.

6.2 Distress Risk Puzzle and Market-to-Book

Griffin and Lemmon (2002) find, using O-score as a measure of distress, that the distress risk puzzle is driven primarily by growth firms, and in particular by the abysmal performance of distressed growth companies. Griffin and Lemmon interpret this evidence as favoring the mispricing explanation of the distress risk puzzle, suggesting that investors overvalue distressed growth firms and underestimate the risks of investing in these firms, which have no pledgable assets and low chances to survive to the time when their bright future prospects are supposed to be realized.

[24]The number of firms in the five quintiles is not the same in single sorts in the rightmost column, because the sorts are performed using NYSE breakpoints.

[25]There are still somewhat more firms in low volatility healthy portfolio than in low volatility distressed portfolio, and the reverse is true for high volatility firms, and as a result low volatility distressed portfolio a bit is underpopulated, and high volatility distressed portfolio is proportionally overpopulated.

The evidence that the distress risk puzzle is coming primarily from growth firms is also consistent with the aggregate volatility risk explanation of the distress risk puzzle. This explanation has it that option-like firms are hedges against aggregate volatility increases. Firms can be option-like if their equity is like a call option on the assets (distressed firms) and also if they own options (growth firms). If a firm is both growth and distressed (i.e., its equity is an option on an option), it will be most option-like and hence the best hedge against aggregate volatility risk, which can explain why average returns to distressed growth firms are so low.

Alternatively, one can say that the double sorting on market-to-book and distress performed by Griffin and Lemmon (2002), is in fact sorting on (different dimensions of) option-likeness and thus sorting on aggregate volatility risk twice, and this is what explains their findings that the distress risk puzzle is driven primarily by growth firms, in particular by distressed growth firms.

Table 5 performs double sorts on my preferred measure of distress (credit rating) and market-to-book. The sorts are conditional in order to break the strong link between market-to-book and credit rating: well-performing firms tend to have high market-to-book and good credit rating. This link is particularly important in my case, since my proposed mechanism behind the distress risk puzzle can also predict that growth firms will be hedges against volatility risk (see Barinov and Chabakauri, 2019, for more evidence and discussion), and thus it is important to control for market-to-book while sorting on distress. In a sense, the distress risk puzzle in Table 5 is a clean version of itself, purged of the confounding effect of market-to-book.

In Panels A1 and B1 of Table 5 that report the CAPM and Carhart alphas, respectively, I observe that the distress risk effect exists exclusively in the growth subsample, in which it is driven by very low alphas of distressed growth firms. This is consistent with both the evidence in Griffin and Lemmon (2002) and my explanation of the distress risk puzzle.

The rest of Table 5 presents the discriminating test between my explanation of the distress risk puzzle and the explanation suggested in Griffin and Lemmon (2002). In Panels A2 and B2, I present the alphas from the ICAPM and Carhart model augmented with the FVIX factor (Carhart+V). I observe that, consistent with my explanation of the distress risk puzzle, but not with the mispricing argument in Griffin and Lemmon (2002), aggregate volatility risk can largely explain both the strong distress risk puzzle in the growth subsample and the difference in the distress risk puzzle between growth and value firms.

The comparison of Panels A1 and A2 is the most striking: in the CAPM alphas, the distress risk puzzle for growth firms is at 86 bp per month, 46 bp per month above that for value firms. Controlling for aggregate volatility risk reduces those two numbers to 11.1 and 11.3 bp per month. The large negative alpha of distressed growth firms sees a similarly drastic reduction from -52 bp in Panel A1 to just -4 bp per month in Panel A2.

Panels A3 and B3 report FVIX betas and confirm that the healthy-minus-distressed strategy indeed has significantly stronger exposure to aggregate volatility risk in the growth subsample. Also, the FVIX beta of distressed growth firms is by far the largest positive FVIX beta in the double sorts on credit rating and market-to-book, indicating their hedging ability against increases in aggregate volatility.

Table 5 also looks at the value effect across distress risk groups, as Griffin and Lemmon (2002) do. Panels A1 and B1 show that the value effect is confined to the three quintiles with the worst credit rating (usually below BBB), consistent with Griffin and Lemmon (2002) and Avramov et al. (2013). The value effect for distressed firms remains visible even in the Carhart alphas, which control for the HML factor.

The stronger value effect for distressed firms is also consistent with my mechanism: Panels A3 and B3 reveal that indeed, the value-minus-growth strategy has a significant exposure to aggregate volatility risk only for the most distressed firms. This is the reason why in Panels A2 and B2, which look at the alphas controlling for FVIX, the value effect for the most distressed firms is significantly reduced compared to Panels A1 and B1.

Panel C and D of Table 5 tabulate average credit rating and average number of firms in each of the fifteen double sorted portfolios. Portfolios seem balanced in terms of number of observations, with distressed growth and distressed neutral portfolios having more firms than other portfolios, but the latter fact is largely caused by the use of NYSE breakpoints, which make the worst credit rating quintile the largest one in single sorts as well.

Credit rating depends positively on market-to-book, especially among healthy firms. That leads to the quintile spread in credit rating to be 2-3 notches larger in growth firms subsample - but on the other hand the average credit rating of the most distressed firms is roughly the same in the value and growth firms subsample, and since the distress risk puzzle is primarily on the short side, the difference in the quintile spread in credit rating between value and growth firms is unlikely to result in a large mechanical difference in the similar alpha spreads.

In Section 2.2 of online Robustness Appendix, I repeat the analysis in Table 5 replacing credit rating with O-score, which makes the results easier to compare with Griffin and Lemmon (2002), who also perform double sorts on O-score and market-to-book. The results very similar to Table 5, indicating that the relation between the distress risk puzzle and market-to-book and its aggregate volatility risk explanation do not depend on which measure of distress one uses.

6.3 Distress Risk Puzzle and Leverage

The hedging power created by existence of risky debt should not exist for zero-leverage firms. More than 95% of firms that have credit rating also have debt, but O-score can be computed for any firm, including a zero-leverage one. Many studies starting with Dichev (1998) sort firms on O-score and include zero-leverage firms in their sample.

Table 6 sorts firms on leverage and then, within each leverage group, into O-score quintiles. I separate zero-leverage firms into a separate group and sort positive-leverage firms into top 30%, middle 40%, and bottom 30%. I predict that sorting zero-leverage firms on O-score will not produce any spread in the CAPM alphas or FVIX betas.[26] For firms with non-zero leverage, O-score captures estimated bankruptcy probability that is imperfectly correlated with leverage: some high leverage firms can still have low probability of going bankrupt, and such firms would not be good hedges against aggregate volatility

[26] As Hasanhodzic and Lo (2018) show, volatility of zero-leverage firms still reacts positively to bad news about firm value, so it is interesting to check if this increase in volatility in bad times has differential effects on firm value of zero-leverage firms depending on O-score.

risk, since the option-likeness of their equity is very unlikely to come into play. Thus, I expect that sorting on O-score within leverage quintiles will still produce a spread in CAPM alphas and FVIX betas, but I do not have a strong prior as to whether those spreads will differ in various leverage groups.

Panel A reports the Carhart alphas and finds that sorting on O-score creates a -2 bp per month alpha spread in the zero-leverage group, which is significantly different from the similar spread of 48 bp per month in the top leverage group. In the other two leverage groups, the distress risk puzzle is close to the one in the top leverage group.

Panel C reports FVIX betas from the Carhart model augmented with FVIX (Carhart+V in the table) and finds that the betas align with the Carhart alphas in Panel A. In particular, the FVIX beta of the healthy-minus-distressed portfolio in the zero-leverage group is -0.159, t-statistic -1.01, as compared to the FVIX betas of similar long-short portfolios in the positive-leverage groups, which are all statistically significant and range between -0.42 and -0.73. Panel B further confirms that adding FVIX to the Carhart model eliminates the distress risk puzzle in all leverage groups.

I conclude that sorting on O-score in the zero-leverage subsample creates no distress risk puzzle and no spread in FVIX betas, as my explanation of distress risk puzzle would predict. In contrast, sorting levered firms on O-score produces a significantly greater distress risk puzzle and spread in FVIX betas, and the latter spread seems to be positively related to leverage.[27]

7 Robustness and More Alternative Explanations

7.1 Distress Risk Puzzle around Downgrades

Avramov et al. (2009a, 2013) show that the distress risk puzzle disappears if the six months before and after credit rating downgrades are excluded from the sample. Avramov

[27]Section 7 of Robustness Appendix also looks at operating leverage, which can potentially have a confounding effect in leverage sorts if firms with high operating leverage choose low financial leverage and operating leverage is related to aggregate volatility risk as another source of convexity in the firm value. Robustness Appendix finds, however, that relation between operating leverage and distress is not strong and that operating leverage is not related to FVIX betas. Thus, operating leverage is unlikely to have a confounding effect on the results in Table 6.

et al. argue that this evidence is inconsistent with a risk-based explanation of the distress risk puzzle: if distressed firms are low-risk, they should have lower expected returns than healthy firms in most periods, not only in the short period around a downgrade that does not happen during the holding period for the vast majority of firms.

In Section 3.1 of online Robustness Appendix,[28] I find that the disappearance of the distress risk puzzle when the time around downgrade is removed is largely look-ahead bias. First, I show that the distress risk puzzle is restored if the six months after downgrade are not removed. As Avramov et al. (2013) show, firms with bad credit rating witness more frequent and more severe downgrades and subsequent delistings for performance reasons. Hence, returns to distressed firms will exhibit a higher upward bias than returns to healthy firms if future downgrades are removed from the sample.

Second, I find that the relation between credit rating and FVIX betas is intact even if months around the downgrade are removed. The main argument in Avramov et al. is that the distress risk puzzle should not be realized around downgrades only, because if healthy firms beat distressed firms due to higher risk of healthy firms, this risk premium should be seen for most firms most of the time. This argument, however, implicitly assumes that no alpha differential equals no risk premium, which is only true if the model used to compute the alphas controls for risk appropriately. The existence of FVIX beta differential between healthy and distressed firms irrespective of whether downgrades are omitted or not contradicts this implicit assumption.

7.2 Distress Risk Puzzle and Negative Earnings

Avramov et al. (2022) show that the distress risk puzzle exists only for firms with negative earnings in the preceding quarter and is driven exclusively by large negative alphas of negative-earnings firms with bad credit rating. Avramov et al. interpret this evidence as suggestive that the distress risk puzzle arises because investors underreact to distress.

Stronger distress risk puzzle for more distressed (negative-earnings) firms is also consistent with my aggregate volatility risk explanation. The more distressed the firm becomes,

[28] Available at https://www.dropbox.com/s/6rb5o3t9abxiv52/Robustness blind.pdf?dl=0

the more option-like its equity is, and the stronger is the hedging ability of equity against aggregate volatility risk.

Consistent with that, in Section 3.2 of online Robustness Appendix I find that FVIX beta of the worst credit rating quintile is 2-3 times more positive for negative-earnings firms than for positive-earnings firms. I also find that FVIX can explain around 50% of the distress risk puzzle for negative-earnings firms and 70-80% of the alpha of negative-earnings firms in the worst credit rating quintile, leaving the rest at most marginally significant at the 10% level and usually insignificant.

7.3 Alternative Distress Measures

Prior research on the distress risk puzzle uses a long list of distress measures. Table 1 shows that sorting firms on credit rating also produces a strong sort on several alternative distress measures, thus implying that if credit rating is related to FVIX betas, and this relation explains the negative link between credit rating and expected returns, then the same will be true if we use other distress measures to evaluate the distress risk puzzle.

Section 1 of online Robustness Appendix uses the two most popular distress measures - O-score from Ohlson (1980) and expected default frequency (EDF) based on Merton (1974) as estimated by Bharath and Shumway (2008). FVIX betas reveal that both O-score and EDF are strongly positively related to FVIX betas, as expected. Controlling for FVIX reduces the O-score-based and EDF-based distress risk puzzle by 25-35 bp per month depending on the baseline model used (CAPM/Carhart), which, on average, constitutes about 90% of its original value. A similar reduction is observed for the negative alpha of most distressed quintile, which creates the majority of the distress risk puzzle.

7.4 Distress Risk Puzzle and Funds from Operations

Kim (2013) breaks down O-score into its components and finds that in conditional sorts O-score is subsumed by its single component, funds from operations over total assets (FFO). Kim (2013) then proceeds to link the explanatory power of both O-score and FFO to the accrual anomaly of Sloan (1996).

In Section 3.3 of online Robustness Appendix, I find that sorting on FFO creates the high-minus-low alpha spread of roughly 45 bp per month. The low-minus-high alpha spread is reduced to statistically insignificant 15-21 bp per month controlling for FVIX. I also observe that the lowest FFO quintile (mainly distressed firms) loads positively on FVIX. Thus, my explanation of distress risk puzzle is consistent with the evidence in Kim (2013): FFO does explain the relation between O-score and expected returns, but the relation between FFO and expected returns is in turn explained by FVIX.

Further analysis suggests that the result in Kim (2013) that FFO subsumes the distress risk puzzle is specific to O-score. When I make sorts on credit rating conditional on FFO, I observe the healthy-minus-distressed alpha spread that is very close to what it was in unconditional sorts.

7.5 Distress Risk Puzzle in Conditional CAPM

O'Doherty (2012) shows that Conditional CAPM (CCAPM) can reduce the distress risk puzzle to statistically insignificant values (which remain economically sizeable at 35-50 bp per month). The evidence in O'Doherty (2012) that the market beta of distressed firms is procyclical is consistent with my explanation of the distress risk puzzle. My paper, however, takes several additional steps ahead compared to O'Doherty (2012): first, it considers the wealth effects of procyclical betas of distressed firms (i.e., smaller losses in bad times). Second, it links those wealth effects to a specific state variable (VIX) and thus suggests adding a new factor and using ICAPM instead of CCAPM. Third, my paper generates cross-sectional predictions about the distress risk puzzle and its volatility risk explanation (see Tables 4 and 5). Fourth, in Table 2 in the paper, the ICAPM makes the distress risk puzzle negative and insignificant.

In Section 9.2 of online Robustness Appendix, I add FVIX to the different versions of the CCAPM to gauge the overlap between the conditioning variables and FVIX. Compared to the ICAPM, controlling for the conditioning variables changes the low-minus-high alpha by 1-12 bp per month, whereas adding FVIX to the CCAPM changes the low-minus-high alpha by full 60 bp per month. FVIX betas of distressed firms or the healthy-minus-distressed portfolio decrease by 12-20% if I make the market beta in the ICAPM conditional. I conclude that the Conditional CAPM explanation of the distress risk puzzle studied in O'Doherty (2012) plays a minor role relative to the aggregate volatility risk explanation studied in Panels A and B of Table 2.

Section 9.2 of online Robustness Appendix also confirms, extending O'Doherty (2012), that the conditional market beta of the healthy-minus-distressed portfolio becomes more countercyclical (and hence the said portfolio becomes more risky) if the portfolio is formed in the high idiosyncratic volatility/analyst disagreement subsample.

In Section 9.3 of online Robustness Appendix, I also experiment with making the FVIX beta conditional; I do find that FVIX beta of the healthy-minus-distressed portfolio is more negative during recessions, but the effect of making the FVIX beta conditional on the alpha of the healthy-minus-distressed portfolio is within 10 bp per month.

7.6 Distress Risk Puzzle and Short-Run/Long-Run Volatility

McQuade (2018) presents a real-options model with stochastic volatility and endogenous default, which predicts that distressed firms will be hedges against volatility risk. The intuition in the model is similar to mine: distress makes the option to default more important, and any option's value increases with volatility, all else equal. McQuade solves the model using asymptotic expansions, and this technical method leads him to assume that it is long-run shocks to volatility that are priced and impact distressed firms differently than other firms.

While the empirical work in my paper can be thought of as an empirical test of McQuade (2018), my state variable is VIX, which is implied volatility of one-month options on the market, i.e., short-run volatility. Hence, at least formally, McQuade (2018) and this paper disagree on whether it is the short-run or long-run part of volatility that matters.

Adrian and Rosenberg (2008) use the Component GARCH (C-GARCH) model and divide C-GARCH forecast of market volatility into the short-run, SR, component (that mean-reverts fast) and long-run, LR, component (that mean-reverts extremely slowly). They find that both components are priced.

In Section 9.1 of online Robustness Appendix, I look at the healthy-minus-distressed strategy for the full sample and for the subsamples in which its alpha is the largest (volatile firms, growth firms, etc.) ICAPM generates (absolute) average alpha of (15) 7 bp per month, and none of the alphas are significant. The Adrian-Rosenberg model with the market factor and the long-run and short-run volatility factors produces average alpha of 50 bp – some improvement over CAPM, but far from the two-factor ICAPM with the market and FVIX. The SR beta is negative and almost always significant, while the LR beta is positive and significant, indicating that the positive-alpha healthy-minus-distressed portfolios are hedges against increases in long-run volatility (in contrast to what the model in McQuade, 2018, predicts).

When I add FVIX to the Adrian-Rosenberg ICAPM, I find overlap between FVIX and SR: FVIX beta drops by about one-third in the presence of SR, and SR beta drops by roughly 20% in the presence of FVIX. I conclude that FVIX has a significant overlap with the short-run volatility risk factor (SR), suggesting that VIX is just a cleaner proxy for expected short-run volatility than C-GARCH forecast.

7.7 Distress Risk Puzzle and Alternative FVIX Versions

The baseline FVIX used in the paper uses, as base assets, quintile portfolios pre-sorted on historical return sensitivity to VIX changes. In Section 4.1 of online Robustness Appendix, I also use two-by-three sorts on size and market-to-book (creating FVIX6) or ten Fama-French (1997) industry portfolios (creating FVIXind) as alternative base assets. Industry portfolios are a particularly stringent robustness check, since they are known to have little factor structure.

The alpha of FVIXind is similar to the alpha of baseline FVIX at about -50 bp per month. The alpha of FVIX6 is smaller at roughly -30 bp per month. FVIX6 and FVIXind betas of the healthy-minus-distressed portfolio are always significantly negative and more negative in growth and high volatility subsample than in value and low volatility subsample. FVIX6 betas are very similar in magnitude to FVIX betas, while FVIXind betas are roughly 30% smaller. Consistent with that, the ICAPM alphas of the healthy-minus-distressed strategy are almost always insignificant when I use FVIX6 or FVIXind instead of the baseline FVIX, though the ability of FVIX6 or FVIXind to explain the CAPM alpha roughly 25-30% smaller than that of FVIX.

Similar evidence emerges when I try to remove confounding factor structure from FVIX in a different way: by dropping distressed (and then also volatile firms) from the base assets. This exercise makes sure than FVIX does not explain the distressed risk puzzle due to a strong tilt away from distressed stocks within FVIX.[29] I find that removing distressed and volatile firms from the base assets does not materially affect the alpha of the resulting alternative FVIX or its ability to explain the distress risk puzzle.

The baseline FVIX is constructed using a single, full-sample factor-mimicking regression. While this is a standard technique of factor-mimicking since Breeden et al. (1989), potential look-ahead bias may be a concern. On the other hand, the look-ahead bias may be absent if investors are more informed than the econometrician. For example, the VIX index starts in January 1986, but investors most probably were learning expected market volatility through other means long before that and may have figured out the way to map its innovations into return space.

In Section 4.2 of online Robustness Appendix, I construct a fully tradable version of FVIX, called FVIXT, using expanding-window regression. I use the first five years in the sample as the learning sample and keep adding new data as time goes by. I find that FVIXT has an even larger alpha than FVIX, around -55 bp per month. Using FVIXT instead of FVIX still produces significantly negative volatility betas of the healthy-minus-distressed strategy and reduces the alphas to insignificant values. The FVIXT betas are roughly 40% smaller than FVIX betas, and the reduction in the alphas is roughly 30% smaller when I use FVIXT instead of FVIX.

7.8 Distress Risk Puzzle and Sentiment

In Section 11 of online Robustness Appendix, I look at potential overlap between FVIX and two new mispricing factors, MGMT and PERF, introduced by Stambaugh and Yuan

[29]It is worth noting that such tilt, if it exists, would also be a strong confirmation of my main hypothesis that firm-specific distress measures are strongly correlated with aggregate volatility risk exposures.

(2017). I find that both factors load negatively on FVIX, and FVIX loads negatively on MGMT and PERF, but neither FVIX is able to explain alphas of MGMT and PERF, nor MGMT and PERF can explain the alpha of FVIX. Consistent with that, in the regressions of various versions of the healthy-minus-distressed strategy on FVIX, MGMT and PERF all factors stay significant in the presence of the others. While this evidence suggest that mispricing factors do play a role in explaining the distress risk puzzle, in the context of this paper a bigger message is that the aggregate volatility risk explanation and the sentiment explanation of the distress risk puzzle have little overlap and are distinct from each other, though not mutually exclusive.

Stambaugh, Yu and Yuan (2012) also use the sentiment index from Baker and Wurgler (2006) to explain the performance of several anomalies. In the same section of online Robustness Appendix, I find that various versions of the healthy-minus-distressed strategy consistently load positively and significantly on the Baker-Wurgler factor. The positive loadings suggest, somewhat surprisingly, that the distress risk puzzle is stronger in periods of high sentiment, when distress is unlikely. This is seems at odds with Avramov et al. (2009a, 2013, 2022) results that the distress risk puzzle is realized during periods of distress. More importantly for my aggregate volatility risk explanation of the distress risk puzzle, I find virtually zero overlap between the FVIX factor and the Baker-Wurgler sentiment factor: the loadings of the healthy-minus-distress portfolios on either factor do not depend on whether the factors are used alone or together.

8 Conclusion

This paper shows that distressed firms tend to perform relatively well when aggregate volatility unexpectedly increases. Since distressed firms have high market betas, they still lose more than an average firm during high volatility periods, which are also periods of declining market, but distressed firms do not lose as much as firms with similarly high market betas when aggregate volatility goes up.

The tendency of distressed firms to outperform the CAPM prediction (or the prediction of other factor models like the Fama-French or Carhart model) during volatile periods explains why distressed firms have negative CAPM/Fama-French/Carhart alphas. Once the lower aggregate volatility risk of distressed firms is controlled for, the alpha differential between healthy and distressed firms (usually referred to as the distress risk puzzle) disappears. This conclusion is invariant to the benchmark model used to compute the alphas and the distress measure used to sort firms into healthy and distressed.

The economic mechanism at work is two-fold. First, the equity of distressed firms can be thought of as the call option on the assets (with the strike price equal to the face value of debt) due to limited liability. All else equal, higher volatility makes the value of option-like equity greater, hence the relatively good performance of distressed firms' equity when aggregate volatility increases.

Second, as Johnson (2004) shows, higher volatility also makes the beta of option-like equity smaller. Based on the Johnson's result, this paper points out that in high volatility periods the declining conditional beta of distressed firms implies a smaller increase in their future discount rates and a smaller drop in their value, giving another reason why option-like equity of distressed firms does relatively well when aggregate volatility increases.

Consistent with my explanation of the distress risk puzzle, I find that the aggregate volatility risk factor can explain why the distress risk puzzle is stronger for volatile firms, which are likely to see greater increases in their volatility and greater positive effects to their value if aggregate volatility increases.

Also consistent with my explanation of the distress risk puzzle is the fact that aggregate volatility risk can explain why the distress risk puzzle is stronger for growth firms (and also why the value effect is stronger for distressed firms) - sorting on market-to-book and then on distress is effectively sorting on option-likeness twice, and sorting more option-like (growth) firms on option-likeness (distress) obviously creates a wider spread in option-likeness.

References

[1] Adrian, T., Rosenberg, J., 2008, Stock Returns and Volatility: Pricing the Short-Run and Long-Run Components of Market Risk, Journal of Finance 63, 2997–3030.

[2] Akbas, F., Boehmer, E., Genc, E. and Petkova, R., 2010, The Time-Varying Liquidity Risk of Value and Growth Stocks, Working paper.

[3] Altman, E. I., 1968, Financial Ratios, Disriminant Analysis, and the Prediction of Corporate Bankruptcy, Journal of Finance 23, 589–609.

[4] Ang, A., Hodrick, R., Xing, Y., Zhang, X., 2006. The Cross-Section of Volatility and Expected Returns. Journal of Finance 61, 259-299.

[5] Avramov, D., Chordia T., Jostova, G. and Philipov, A., 2009a, Credit Ratings and the Cross-Section of Stock Returns, Journal of Financial Markets 12, 469–499.

[6] Avramov, D., Chordia T., Jostova, G. and Philipov, A., 2009b, Dispersion in Analysts' Earnings Forecasts and Credit Rating, Journal of Financial Economics 91, 83–101.

[7] Avramov, D., Chordia T., Jostova, G. and Philipov, A., 2013, Anomalies and Financial Distress, Journal of Financial Economics 81, 139–159.

[8] Avramov, D., Chordia T., Jostova, G., and Philipov, A., 2022, The Distress Anomaly is Deeper than you Think: Evidence from Stocks and Bonds, Review of Finance 26, 355–405.

[9] Baker, M., Wurgler, J., 2006, Investor Sentiment and the Cross-Section of Stock Returns, Journal of Finance 61, 1645–1680.

[10] Bali, T., Cakici, N. and Whitelaw, R., 2011, Maxing Out: Stocks as Lotteries and the Cross-Section of Expected Returns, Journal of Financial Economics, 99, 427–446.

[11] Barinov, A., 2012, Aggregate Volatility Risk: Explaining the Small Growth Anomaly and the New Issues Puzzle, Journal of Corporate Finance 18, 763–781.

[12] Barinov, A., 2013, Analyst Disagreement and Aggregate Volatility Risk, Journal of Financial and Quantitative Analysis 48, 1877–1900.

[13] Barinov, A., 2022. Profitability Anomaly and Aggregate Volatility Risk. Journal of Financial Markets, forthcoming.

[14] Barinov, A., 2017. Institutional Ownership and Aggregate Volatility Risk. Journal of Empirical Finance 40, 20-38.

[15] Barinov, A., 2018, Stocks with Extreme Past Returns: Lotteries or Insurance? Journal of Financial Economics 129, 458–478.

[16] Barinov, A., Chabakauri, G., 2019, Idiosyncratic Volatility, Growth Options, and the Cross-Section of Returns, Working paper.

[17] Barinov, A., Xu, J., Pottier, S. W., 2020. Estimating the Cost of Equity Capital for Insurance Firms with Multi-period Asset Pricing Models, Journal of Risk and Insurance 87, 213–245.

[18] Bartram, S. M., Brown, G., Stulz, R. M., 2016. Why does Idiosyncratic Risk Increase with Market Risk? NBER Working Paper 22492.

[19] Boguth, O., Carlson, M., Fisher, A., Simutin, M., 2011, Conditional Risk and Performance Evaluation: Volatility Timing, Overconditioning, and New Estimates of Momentum Alphas, Journal of Financial Economics 102, 363–389.

[20] Bharath, S. T., Shumway, T., 2008, Forecasting Default with the Merton Distance to Default Model, Review of Financial Studies 21, 1339–1369.

[21] Breeden, D. T., Gibbons, M. R., Litzenberger, R. H., 1989, Empirical Test of the Consumption-Oriented CAPM, Journal of Finance 44, 231–262.

[22] Brennan, M., Chordia, T., and Subrahmanyam, A., 1998, Alternative Factor Specifications, Security Characteristics and the Cross-Section of Expected Returns, Journal of Financial Economics 49, 345–374.

[23] Campbell, J. Y., 1993, Intertemporal Asset Pricing without Consumption Data, American Economic Review 83, 487–512.

[24] Campbell, J., Lettau, M., Malkiel, B., Xu, Y., 2001. Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk. Journal of Finance 56, 1-43.

[25] Campbell, J. Y., Hilscher, J. and Szilagyi, J., 2008, In Search of Distress Risk, Journal of Finance 63, 2899–2939.

[26] Campbell, J. Y., Giglio, S., Polk, C. and Turley, R., 2018, An Intertemporal CAPM with Stochastic Volatility, Journal of Financial Economics 128, 207–233.

[27] Carhart, M. M., 1997, On the Persistence in Mutual Funds Performance Journal of Finance 52, 57–82.

[28] Chen, J., 2002, Intertemporal CAPM and the Cross-Section of Stock Returns, Working paper.

[29] Chen, J., Cholette, L., and Ray R., 2010, Financial Distress and Idiosyncratic Volatility: An Empirical Investigation, Journal of Financial Markets 13, 249-267

[30] Conrad, J., Kapadia, N., Xing, Y., 2014, Death and Jackpot: Why do Individual Investors Hold Overpriced Stocks? Journal of Financial Economics 113, 455–475.

[31] Daniel, K., and Titman, S., 2006, Market Reactions to Tangible and Intangible Information, Journal of Finance 61, 1605–1643.

[32] Dichev, I. D., 1998, Is the Risk of Bankruptcy a Systematic Risk? Journal of Finance 53, 1131–1147.

[33] Diether, K., Malloy, C. and Scherbina, A., 2002, Differences of Opinion and the Cross-Section of Returns, Journal of Finance 57, 2113–2141.

[34] Duarte, J., Kamara, A., Siegel, S., Sun, C., 2012, The Common Components of Idiosyncratic Volatility, Working paper.

[35] Eckbo, B. E., Masulis, R. W., and Norli, Ø., 2000, Seasoned Public Offerings: Resolution of the New Issues Puzzle, Journal of Financial Economics 56, 251–291.

[36] Eisdorfer, A., Misirli, E. U., 2020, Distressed Stocks in Distressed Times, Management Science 66, 2452—2473.

[37] Fama, E. F., French, K. R., 1993, Common Risk Factors in the Returns on Stocks and Bonds, Journal of Financial Economics 33, 3–56.

[38] Fama, E. F., French, K. R., 1997, Industry Costs of Equity, Journal of Financial Economics 43, 153–193.

[39] Fama, Eugene F., and Kenneth R. French, 2015, A Five-Factor Asset Pricing Model, Journal of Financial Economics 116, 1–22.

[40] Garlappi, L., Shu, T., and Yan, H., 2008, Default Risk, Shareholder Advantage, and Stock Returns, Review of Financial Studies 21, 2743–2778.

[41] George, T. J., and Hwang, C.-Y., 2010, A Resolution of the Distress Risk and Leverage Puzzles in the Cross-Section of Stock Returns, Journal of Financial Economics 96, 56–79.

[42] Griffin, J. M., and Lemmon, M. L., 2002, Book-to-Market Equity, Distress Risk, and Stock Returns, Journal of Finance 57, 2317–2336.

[43] Grullon, G., Lyandres, E., and Zhdanov, A., 2012, Real Options, Volatility, and Stock Returns, Journal of Finance 67, 1499–1537.

[44] Jegadeesh, N., 1990, Evidence of Predictable Behavior of Security Returns, Journal of Finance 45, 881–898.

[45] Johnson, T. C., 2004, Forecast Dispersion and the Cross-Section of Expected Returns, Journal of Finance 59, 1957–1978.

[46] Hahn, J., Lee, H., 2006, Yield Spreads as Alternative Risk Factors for Size and Book-to-Market, Journal of Financial and Quantitative Analysis 41, 245–270.

[47] Hasanhodzic, J., Lo, A. W., 2018, On Black's Leverage Effect in Firms With No Leverage, Working paper.

[48] Herskovic, B., Kelly, B., Lustig, H., and van Neuwerburgh, S., 2016, The Common Factor in Idiosyncratic Volatility: Quantitative Asset Pricing Implications, Journal of Financial Economics 119, 249–283.

[49] Kim, S., 2013, What is behind the Magic of O-Score? An Alternative Interpretation of Dichev's (1998) Bankruptcy Risk Anomaly, Review of Accounting Studies 18, 291–323.

[50] McQuade, T. J., 2018, Stochastic Volatility and Asset Pricing Puzzles, Working paper.

[51] Merton, R. C., 1974, On the Pricing of Corporate Debt: The Risk Structure of Interest Rates, Journal of Finance 29, 449–470.

[52] Newey, W. K., West, K. D., 1987, A Simple Positive Semi-Definite Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, Econometrica 55, 703–708.

[53] O'Doherty, M.S., 2012, On the Conditional Risk and Performance of Financially Distressed Stocks, Management Science 58, 1502–1520.

[54] Ohlson, J. A., 1980, Financial Ratios and the Probabilistic Prediction of Bankruptcy, Journal of Accounting Research 18, 109–131.

[55] Pastor, L., Stambaugh, R. F., 2003, Liquidity Risk and Expected Stock Returns, Journal of Political Economy 111, 642–685.

[56] Petkova, R., 2006, Do the Fama-French Factors Proxy for Innovations in Predictive Variables? Journal of Finance 61, 581–612.

[57] Petkova, R., and Zhang, L., 2005, Is Value Riskier than Growth? Journal of Financial Economics 78, 187–202.

[58] Sloan, R. G., 1996, Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings? Accounting Review 71, 289–315.

[59] Stambaugh, R. F., Yu, J., Yuan, Y., 2012, The Short of it: Investor Sentiment and Anomalies, Journal of Financial Economics 104, 288–302.

[60] Stambaugh, R. F., Yuan, Y., 2017, Mispricing Factors, Review of Financial Studies 30, 1270–1315.

Table 1. Descriptive Statistics

Panel A looks at median values of distress measures - O-score, Z-score (a measure of financial health), expected default frequency (EDF) from Merton (1974), and market leverage (Lev) - across credit rating quintiles. Panel B reports, for the same quintiles, median values of several firm-specific uncertainty measures - idiosyncratic volatility (IVol), analyst disagreement (Disp), analyst forecast error (Error), volatility of cash flows (CVCFO) and earnings (CVEarn). Panel C looks at the median values of "catch-all" measures of firm value convexity from Grullon et al. (2012). Panel D performs firm-level univariate regressions of simple and then percentage change in IVol (Disp) on change in VIX and then reports average slopes within credit rating quintiles. Detailed definitions of all variables are in online Data Appendix. The credit rating quintiles are formed using NYSE (exchcd=1) breakpoints and rebalanced monthly. The top (AveCred) line of each panel reports average credit rating of the quintile. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017. The sample excludes stocks priced below $5 on the portfolio formation date.

Panel A. Credit Rating and Other Distress Measures

	Best	**Cred2**	**Cred3**	**Cred4**	**Worst**	**W-B**	**t(W-B)**
AveCred	*A+*	*BBB+*	*BBB-*	*BB*	*B+*		
OScore	-7.541	-6.822	-6.536	-5.942	-5.169	2.371	*57.1*
ZScore	-3.630	-2.914	-2.595	-2.097	-1.596	2.034	*48.7*
EDF	0.000	0.002	0.009	0.295	1.783	1.783	*2.88*
Lev	0.137	0.211	0.266	0.355	0.443	0.306	*42.7*

Panel B. Credit Rating and Firm-Level Volatility

	Best	**Cred2**	**Cred3**	**Cred4**	**Worst**	**W-B**	**t(W-B)**
AveCred	*A+*	*BBB+*	*BBB-*	*BB*	*B+*		
IVol	0.011	0.013	0.015	0.018	0.023	0.012	*30.5*
Disp	0.021	0.033	0.041	0.058	0.101	0.080	*16.4*
Error	0.049	0.084	0.110	0.149	0.263	0.214	*16.9*
CVEarn	0.390	0.631	0.880	1.240	1.925	1.535	*29.0*
CVCFO	0.541	0.741	0.908	1.041	1.517	0.977	*14.5*

Panel C. Credit Rating and Firm Value Convexity

	Best	**Cred2**	**Cred3**	**Cred4**	**Worst**	**W-B**
AveCred	*A+*	*BBB+*	*BBB-*	*BB*	*B+*	
TVol Sens	-0.564	-2.655	1.046	0.490	4.176	4.740
t-stat	*-0.40*	*-2.45*	*0.87*	*0.62*	*4.99*	*4.78*
SUE flex	0.037	0.072	0.076	0.068	0.096	0.059
t-stat	*6.37*	*9.36*	*10.55*	*8.19*	*12.92*	*5.99*

Panel D. Firm-Specific Uncertainty: Sensitivity to VIX Changes

AveCred	**Best** *A+*	**Cred2** *BBB+*	**Cred3** *BBB-*	**Cred4** *BB*	**Worst** *B+*	**W-B**
$\boldsymbol{\Delta IVol}$	0.021	0.023	0.030	0.034	0.043	0.022
t-stat	*11.2*	*10.4*	*17.2*	*15.4*	*11.9*	*7.62*
% $\boldsymbol{\Delta IVol}$	0.353	0.342	0.413	0.399	0.378	0.025
t-stat	*9.67*	*9.89*	*18.9*	*13.3*	*11.7*	*0.86*
$\boldsymbol{\Delta Disp}$	0.103	-0.290	-0.238	-0.034	1.197	1.094
t-stat	*2.23*	*-1.48*	*-0.92*	*-0.21*	*2.72*	*2.52*
% $\boldsymbol{\Delta Disp}$	0.075	0.042	0.105	0.165	0.419	0.344
t-stat	*2.07*	*1.11*	*2.64*	*3.14*	*4.01*	*4.34*

Table 2. Distress Risk Puzzle and Aggregate Volatility Risk

The table reports value-weighted (Panel A) and equal-weighted (Panel B) alphas from the CAPM, the Carhart model, as well as alphas and FVIX betas from the two-factor ICAPM with the market factor and FVIX, and the Carhart model augmented with FVIX, "Carhart+V". Panels A3 and B3 report alphas and market betas from the Conditional CAPM that uses default premium (Baa-Aaa yield spread), dividend yield of the market portfolio, term spread (yield to 10-year Treasuries minus yield to 1-year Treasuries), and 1-month Treasury bill yield as conditioning variables:

$$\begin{aligned} Ret_t - RF_t &= \alpha + \gamma_0 \cdot (MKT_t - RF_t) + \gamma_1 \cdot DEF_{t-1} \cdot (MKT_t - RF_t) + \gamma_2 \cdot DIV_{t-1} \cdot (MKT_t - RF_t) \\ &\quad + \gamma_3 \cdot TB_{t-1} \cdot (MKT_t - RF_t) + \gamma_4 \cdot TERM_{t-1} \cdot (MKT_t - RF_t) \end{aligned} \tag{3}$$

Market betas from the Conditional CAPM are averaged separately in recessions (β_{Rec}) and expansions (β_{Exp}). Recessions are defined as periods when expected market risk premium, which is the fitted part from

$$MKT_t - RF_t = c_0 + c_1 \cdot DEF_{t-1} + c_1 \cdot DIV_{t-1} + c_3 \cdot TB_{t-1} + c_4 \cdot TERM_{t-1} \tag{4}$$

exceeds in-sample average of market risk premium. The models are fitted to the quintile portfolios sorted on credit rating from month t-2. The quintiles are formed using NYSE (exchcd=1) breakpoints and are rebalanced monthly. The top (AveCred) line of each panel reports average credit rating of the quintile. FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2016. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Panel A. Value-Weighted Returns

A1. CAPM as Benchmark Model

	Best	**Cred2**	**Cred3**	**Cred4**	**Worst**	**B-W**
AveCred	*A+*	*BBB+*	*BBB-*	*BB*	*B+*	
$\boldsymbol{\alpha}_{CAPM}$	0.142	-0.138	-0.007	-0.496	-0.690	0.832
t-stat	*2.12*	*-1.36*	*-0.05*	*-2.98*	*-2.80*	*2.86*
$\boldsymbol{\alpha}_{ICAPM}$	-0.070	-0.038	0.081	-0.300	-0.094	0.024
t-stat	*-0.79*	*-0.42*	*0.57*	*-1.59*	*-0.40*	*0.08*
$\boldsymbol{\beta}_{FVIX}$	-0.456	0.215	0.189	0.421	1.280	-1.736
t-stat	*-4.41*	*2.90*	*1.04*	*2.01*	*6.50*	*-6.87*

Panel B. Equal-Weighted Returns

B1. CAPM as Benchmark Model

	Best	**Cred2**	**Cred3**	**Cred4**	**Worst**	**B-W**
AveCred	*A+*	*BBB+*	*BBB-*	*BB*	*B+*	
$\boldsymbol{\alpha}_{CAPM}$	0.253	0.178	0.146	-0.093	-0.547	0.800
t-stat	*2.57*	*1.36*	*0.82*	*-0.44*	*-2.68*	*3.85*
$\boldsymbol{\alpha}_{ICAPM}$	0.029	0.099	0.136	0.010	-0.130	0.159
t-stat	*0.29*	*0.75*	*0.75*	*0.05*	*-0.57*	*0.73*
$\boldsymbol{\beta}_{FVIX}$	-0.482	-0.170	-0.021	0.221	0.896	-1.378
t-stat	*-2.61*	*-0.89*	*-0.08*	*0.87*	*5.28*	*-6.99*

A2. Carhart Model as Benchmark Model

AveCred	**Best** *A+*	**Cred2** *BBB+*	**Cred3** *BBB-*	**Cred4** *BB*	**Worst** *B+*	**B-W**
$\boldsymbol{\alpha}_{Carhart}$	0.145	-0.037	0.008	-0.366	-0.300	0.444
t-stat	*2.62*	*-0.42*	*0.07*	*-2.46*	*-1.30*	*1.76*
$\boldsymbol{\alpha}_{Carhart+V}$	0.028	0.056	0.075	-0.252	0.064	-0.035
t-stat	*0.47*	*0.69*	*0.67*	*-1.69*	*0.33*	*-0.17*
$\boldsymbol{\beta}_{FVIX}$	-0.260	0.207	0.149	0.253	0.809	-1.068
t-stat	*-3.86*	*2.98*	*1.23*	*1.73*	*5.38*	*-5.73*

B2. Carhart Model as Benchmark Model

AveCred	**Best** *A+*	**Cred2** *BBB+*	**Cred3** *BBB-*	**Cred4** *BB*	**Worst** *B+*	**B-W**
$\boldsymbol{\alpha}_{Carhart}$	0.220	0.148	0.113	-0.116	-0.386	0.606
t-stat	*3.01*	*1.76*	*0.99*	*-0.90*	*-3.35*	*4.35*
$\boldsymbol{\alpha}_{Carhart+V}$	0.040	0.091	-0.013	-0.009	0.047	-0.007
t-stat	*0.61*	*0.97*	*-0.12*	*-0.06*	*0.18*	*-0.03*
$\boldsymbol{\beta}_{FVIX}$	-0.372	-0.265	-0.022	0.248	0.665	-1.037
t-stat	*-3.87*	*-2.88*	*-0.18*	*1.83*	*2.86*	*-3.36*

A3. Conditional CAPM

AveCred	**Best** *A+*	**Cred2** *BBB+*	**Cred3** *BBB-*	**Cred4** *BB*	**Worst** *B+*	**B-W**
$\boldsymbol{\alpha}_{CCAPM}$	0.100	-0.086	-0.081	-0.451	-0.432	0.532
t-stat	*1.48*	*-0.96*	*-0.70*	*-2.84*	*-1.77*	*1.90*
$\boldsymbol{\beta}_{\boldsymbol{Rec}}$	0.915	1.057	1.241	1.294	1.347	-0.432
t-stat	*138.1*	*151.1*	*67.1*	*56.1*	*42.4*	*-12.2*
$\boldsymbol{\beta}_{\boldsymbol{Exp}}$	0.828	1.155	1.091	1.381	1.819	-0.991
t-stat	*73.5*	*125.2*	*58.6*	*67.1*	*44.5*	*-20.7*
$\boldsymbol{\beta}_{\boldsymbol{R}} - \boldsymbol{\beta}_{\boldsymbol{E}}$	0.087	-0.098	0.151	-0.087	-0.473	0.559
t-stat	*6.64*	*-8.07*	*5.46*	*-2.75*	*-8.46*	*8.74*

B3. Conditional CAPM

AveCred	**Best** *A+*	**Cred2** *BBB+*	**Cred3** *BBB-*	**Cred4** *BB*	**Worst** *B+*	**B-W**
$\boldsymbol{\alpha}_{CCAPM}$	0.170	0.103	0.044	-0.189	-0.519	0.688
t-stat	*2.34*	*0.90*	*0.29*	*-1.00*	*-2.42*	*3.26*
$\boldsymbol{\beta}_{\boldsymbol{Rec}}$	1.009	1.139	1.246	1.374	1.423	-0.415
t-stat	*91.3*	*93.7*	*62.5*	*54.0*	*44.4*	*-12.0*
$\boldsymbol{\beta}_{\boldsymbol{Exp}}$	0.822	0.965	1.012	1.149	1.435	-0.613
t-stat	*34.4*	*46.4*	*34.5*	*37.1*	*41.4*	*-17.8*
$\boldsymbol{\beta}_{\boldsymbol{R}} - \boldsymbol{\beta}_{\boldsymbol{E}}$	0.187	0.174	0.234	0.226	-0.011	0.198
t-stat	*6.94*	*6.75*	*6.19*	*5.30*	*-0.23*	*4.01*

Table 3. Cross-Sectional Regressions

The table presents the results of firm-level Fama-MacBeth regressions run each month. The dependent variables, as indicated in the header of each column, are firm-level risk-adjusted returns ($\overline{\alpha}$) estimated as in Brennan et al. (1998) (see online Data Appendix). All independent variables but Cred are ranks between 0 and 1. Cred is coded as AAA=1, AA+=2, ... D=22. In each month and for each variable, all firms are ranked in the ascending order and are assigned a rank, with zero (one) for the firm with the lowest (highest) value of the variable. The controls are market-to-book (MB), size, cumulative return between month t-2 and t-12 (MOM), and past month return (REV). Detailed definitions of all variables are in online Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2016. The sample excludes stocks priced below $5 at the portfolio formation date.

	Raw	$\hat{\boldsymbol{\alpha}}_{CAPM}$	$\hat{\boldsymbol{\alpha}}_{ICAPM}$	$\hat{\boldsymbol{\alpha}}_{FF3}$	$\hat{\boldsymbol{\alpha}}_{FF3+V}$	$\hat{\boldsymbol{\alpha}}_{Carhart}$	$\hat{\boldsymbol{\alpha}}_{Carhart+V}$
Size	-0.766	-0.784	-0.578	-0.637	-0.274	-0.576	-0.188
t-stat	*-1.45*	*-1.72*	*-1.07*	*-1.64*	*-0.52*	*-1.40*	*-0.33*
MB	-0.446	-0.362	-0.138	0.078	0.068	-0.112	-0.233
t-stat	*-1.96*	*-1.58*	*-0.56*	*0.44*	*0.32*	*-0.57*	*-1.01*
Mom	1.002	0.834	0.699	0.506	0.270	0.244	0.413
t-stat	*2.39*	*2.19*	*1.31*	*1.41*	*0.49*	*0.65*	*0.75*
Rev	-0.293	-0.309	-0.567	-0.464	-0.803	-0.546	-0.795
t-stat	*-1.30*	*-1.36*	*-1.83*	*-1.90*	*-2.24*	*-1.83*	*-2.08*
Cred	-4.648	-7.258	-0.215	-6.796	-3.438	-6.331	-3.101
t-stat	*-1.83*	*-3.56*	*-0.09*	*-4.14*	*-1.83*	*-3.82*	*-1.63*

Table 4. Distress Risk Puzzle, Idiosyncratic Volatility, and Aggregate Volatility Risk

Panel A presents CAPM alphas, ICAPM alphas, and FVIX betas for the conditional double sorts first into three groups (bottom 30%, middle 40%, top 30%) on idiosyncratic volatility and then into quintiles on credit rating. The double sorts are repeated each month and use NYSE (exchcd=1) quintiles. Idiosyncratic volatility is the standard deviation of residuals from the Fama-French model, fitted to the daily data for each firm-month (at least 15 valid observations are required). Panel B presents the Carhart alphas, the Carhart+V alphas (from the Carhart model augmented with FVIX), and FVIX betas of the same double-sorted portfolios. FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. Panel C reports average credit rating (coded as AAA=1, AA+=2, ... D=22), and Panel D reports average number of firms in each of the double sorted portfolios. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2016. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Panel A1. CAPM alphas

	Low	**Med**	**High**	**L-H**
Best	0.429	0.244	0.171	0.257
t-stat	*3.99*	*2.31*	*0.99*	*1.50*
Cred2	0.336	0.157	0.155	0.181
t-stat	*2.37*	*1.10*	*0.71*	*1.03*
Cred3	0.378	0.318	-0.243	0.628
t-stat	*2.53*	*1.64*	*-0.88*	*2.61*
Cred4	0.269	0.138	-0.148	0.397
t-stat	*1.38*	*0.66*	*-0.56*	*1.83*
Worst	0.244	0.145	-0.902	1.145
t-stat	*1.35*	*0.69*	*-3.19*	*3.83*
B-W	0.185	0.099	1.073	0.888
t-stat	*1.18*	*0.52*	*3.80*	*2.99*

Panel A2. ICAPM alphas

	Low	**Med**	**High**	**L-H**
Best	0.106	0.047	0.061	0.045
t-stat	*0.97*	*0.41*	*0.29*	*0.21*
Cred2	0.198	0.029	0.452	-0.254
t-stat	*1.33*	*0.19*	*2.16*	*-1.32*
Cred3	0.058	0.248	0.241	-0.183
t-stat	*0.28*	*1.28*	*1.06*	*-1.05*
Cred4	0.474	0.081	0.079	0.395
t-stat	*2.54*	*0.36*	*0.30*	*1.63*
Worst	0.181	0.478	-0.032	0.207
t-stat	*0.61*	*2.14*	*-0.13*	*0.78*
B-W	-0.072	-0.430	0.094	0.169
t-stat	*-0.26*	*-2.03*	*0.34*	*0.59*

Panel A3. FVIX Betas

	Low	**Med**	**High**	**L-H**
Best	-0.674	-0.414	0.136	-0.809
t-stat	*-3.49*	*-2.04*	*0.66*	*-4.67*
Cred2	-0.455	-0.246	0.176	-0.632
t-stat	*-2.12*	*-1.09*	*0.78*	*-3.70*
Cred3	-0.385	-0.131	0.535	-0.927
t-stat	*-1.78*	*-0.44*	*1.64*	*-5.53*
Cred4	-0.277	-0.027	0.800	-1.084
t-stat	*-1.18*	*-0.10*	*5.01*	*-5.27*
Worst	-0.054	0.597	1.496	-1.550
t-stat	*-0.32*	*2.81*	*6.37*	*-6.38*
B-W	-0.620	-1.011	-1.361	-0.741
t-stat	*-4.58*	*-8.05*	*-6.05*	*-3.31*

Panel B1. Carhart alphas

	Low	Med	High	L-H
Best	0.365	0.222	0.259	0.107
t-stat	*4.38*	*2.67*	*1.99*	*0.74*
Cred2	0.285	0.094	0.221	0.064
t-stat	*2.49*	*0.95*	*1.40*	*0.42*
Cred3	0.323	0.256	-0.170	0.514
t-stat	*2.59*	*1.86*	*-0.90*	*2.47*
Cred4	0.151	0.078	-0.028	0.164
t-stat	*0.93*	*0.52*	*-0.16*	*0.88*
Worst	0.133	0.090	-0.593	0.726
t-stat	*0.97*	*0.64*	*-2.59*	*2.57*
B-W	0.232	0.132	0.851	0.619
t-stat	*1.83*	*0.88*	*3.31*	*2.10*

Panel B2. Carhart+V alphas

	Low	Med	High	L-H
Best	0.108	0.078	0.165	-0.057
t-stat	*1.36*	*0.94*	*0.75*	*-0.24*
Cred2	0.127	-0.049	0.442	-0.315
t-stat	*1.19*	*-0.50*	*2.54*	*-1.69*
Cred3	-0.087	0.152	0.201	-0.288
t-stat	*-0.54*	*1.17*	*1.28*	*-1.68*
Cred4	0.227	-0.126	-0.016	0.243
t-stat	*1.45*	*-0.80*	*-0.10*	*1.13*
Worst	0.054	0.215	-0.103	0.148
t-stat	*0.20*	*1.37*	*-0.82*	*0.54*
B-W	0.061	-0.137	0.268	0.207
t-stat	*0.23*	*-0.88*	*1.13*	*0.70*

Panel B3. FVIX Betas

	Low	Med	High	L-H
Best	-0.492	-0.308	0.011	-0.502
t-stat	*-3.80*	*-2.63*	*0.08*	*-3.50*
Cred2	-0.411	-0.289	-0.126	-0.285
t-stat	*-3.16*	*-2.62*	*-0.76*	*-1.60*
Cred3	-0.390	-0.221	0.066	-0.471
t-stat	*-3.23*	*-1.26*	*0.34*	*-3.64*
Cred4	-0.380	-0.264	0.161	-0.545
t-stat	*-2.72*	*-1.44*	*0.99*	*-3.36*
Worst	-0.301	0.157	0.799	-1.100
t-stat	*-2.29*	*0.85*	*4.16*	*-4.83*
B-W	-0.190	-0.465	-0.788	-0.598
t-stat	*-1.46*	*-2.92*	*-3.19*	*-2.22*

Panel C. Average Credit Rating

	Low	Med	High	H-L	Full
Best	2.9	4.5	6.5	3.6	5.1
Cred2	6.3	8.1	10.6	4.3	8.1
Cred3	7.9	9.8	12.5	4.6	10.1
Cred4	9.4	11.4	13.9	4.5	12.1
Worst	11.8	13.7	15.7	3.8	14.4
W-B	9.0	9.2	9.2	0.3	9.3
t-stat	*119.1*	*113.8*	*66.8*	*1.81*	*92.5*

Panel D. Average Number of Observations

	Low	Med	High	H-L	Full
Best	47.5	63.9	48.6	1.1	151.9
Cred2	34.9	52.5	47.6	12.7	143.7
Cred3	37.2	49.4	57.1	20.2	124.9
Cred4	31.0	52.8	62.4	31.3	136.9
Worst	35.8	55.1	53.9	18.0	189.2
W-B	-11.7	-8.8	5.3	16.9	37.2
t-stat	*-12.38*	*-5.17*	*1.40*	*4.61*	*6.53*

Table 5. Distress Risk Puzzle, Market-to-Book, and Aggregate Volatility Risk

Panel A presents CAPM alphas, ICAPM alphas, and FVIX betas for the conditional double sorts first into three groups (bottom 30%, middle 40%, top 30%) on market-to-book and then into quintiles on credit rating. The double sorts on credit rating (market-to-book) are repeated each month (year) and use NYSE (exchcd=1) quintiles. Panel B presents the Carhart alphas, the Carhart+V alphas (from the Carhart model augmented with FVIX), and FVIX betas of the same double-sorted portfolios. FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. Panel C reports average credit rating (coded as AAA=1, AA+=2, ... D=22), and Panel D reports average number of firms in each of the double sorted portfolios. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2016. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Panel A1. CAPM alphas

	Value	**Neut**	**Growth**	**G-V**
Best	0.349	0.335	0.345	0.005
t-stat	*1.91*	*2.29*	*3.41*	*0.03*
Cred2	0.348	0.262	0.187	0.160
t-stat	*1.41*	*1.59*	*1.84*	*0.76*
Cred3	0.165	0.193	0.296	-0.131
t-stat	*0.60*	*0.97*	*2.61*	*-0.50*
Cred4	-0.154	0.100	-0.047	-0.082
t-stat	*-0.60*	*0.48*	*-0.28*	*-0.39*
Worst	-0.053	-0.226	-0.515	0.462
t-stat	*-0.16*	*-0.98*	*-2.66*	*1.47*
B-W	0.403	0.561	0.860	0.457
t-stat	*1.63*	*2.45*	*3.44*	*1.72*

Panel A2. ICAPM alphas

	Value	**Neut**	**Growth**	**G-V**
Best	0.252	0.091	0.072	0.180
t-stat	*1.29*	*0.58*	*0.68*	*0.88*
Cred2	0.418	0.077	0.029	0.389
t-stat	*1.73*	*0.44*	*0.29*	*1.81*
Cred3	0.234	0.054	0.271	-0.036
t-stat	*0.86*	*0.27*	*2.64*	*-0.13*
Cred4	0.082	0.121	0.002	0.096
t-stat	*0.28*	*0.57*	*0.01*	*0.40*
Worst	0.253	0.169	-0.039	0.293
t-stat	*0.72*	*0.68*	*-0.21*	*0.92*
B-W	-0.001	-0.079	0.111	0.113
t-stat	*-0.01*	*-0.33*	*0.45*	*0.42*

Panel A3. FVIX Betas

	Value	**Neut**	**Growth**	**G-V**
Best	-0.210	-0.526	-0.586	0.376
t-stat	*-0.78*	*-2.46*	*-3.10*	*2.32*
Cred2	0.152	-0.399	-0.340	0.491
t-stat	*0.48*	*-1.84*	*-2.04*	*2.76*
Cred3	0.150	-0.298	-0.054	0.204
t-stat	*0.51*	*-1.19*	*-0.44*	*0.96*
Cred4	0.513	0.046	0.106	0.387
t-stat	*1.66*	*0.18*	*0.77*	*1.73*
Worst	0.659	0.849	1.023	-0.364
t-stat	*2.63*	*3.44*	*7.28*	*-1.58*
B-W	-0.869	-1.375	-1.609	-0.740
t-stat	*-3.91*	*-10.03*	*-5.76*	*-3.98*

Panel B1. Carhart alphas

	Value	Neut	Growth	G-V
Best	0.321	0.282	0.332	-0.011
t-stat	*2.79*	*2.78*	*3.67*	*-0.09*
Cred2	0.320	0.207	0.176	0.144
t-stat	*1.74*	*1.72*	*1.79*	*0.87*
Cred3	0.140	0.113	0.328	-0.188
t-stat	*0.77*	*0.85*	*3.02*	*-0.96*
Cred4	-0.204	0.045	-0.015	-0.150
t-stat	*-1.17*	*0.28*	*-0.11*	*-0.73*
Worst	0.134	-0.149	-0.322	0.456
t-stat	*0.63*	*-0.91*	*-1.93*	*1.66*
B-W	0.187	0.431	0.653	0.467
t-stat	*0.93*	*2.18*	*3.19*	*1.63*

Panel B2. Carhart+V alphas

	Value	Neut	Growth	G-V
Best	0.248	0.087	0.151	0.097
t-stat	*2.35*	*0.89*	*1.73*	*0.78*
Cred2	0.345	0.004	0.040	0.305
t-stat	*2.00*	*0.04*	*0.44*	*1.83*
Cred3	0.084	-0.081	0.230	-0.146
t-stat	*0.46*	*-0.62*	*2.27*	*-0.71*
Cred4	-0.072	-0.054	-0.098	0.050
t-stat	*-0.43*	*-0.36*	*-0.71*	*0.24*
Worst	0.190	-0.017	-0.141	0.331
t-stat	*0.87*	*-0.11*	*-1.03*	*1.25*
B-W	0.057	0.104	0.291	0.234
t-stat	*0.27*	*0.62*	*1.68*	*0.82*

Panel B3. FVIX Betas

	Value	Neut	Growth	G-V
Best	-0.163	-0.435	-0.403	0.240
t-stat	*-1.70*	*-4.80*	*-2.30*	*1.43*
Cred2	0.056	-0.457	-0.302	0.358
t-stat	*0.37*	*-4.53*	*-2.23*	*2.95*
Cred3	-0.125	-0.431	-0.219	0.094
t-stat	*-0.81*	*-3.22*	*-1.75*	*0.68*
Cred4	0.305	-0.221	-0.185	0.464
t-stat	*1.79*	*-1.22*	*-1.40*	*2.83*
Worst	0.125	0.294	0.403	-0.278
t-stat	*0.60*	*1.33*	*2.49*	*-1.15*
B-W	-0.288	-0.728	-0.806	-0.518
t-stat	*-1.35*	*-3.82*	*-3.71*	*-2.62*

Panel C. Average Credit Rating

	Value	Neut	Growth	V-G	Full
Best	7.2	5.5	3.8	3.4	5.1
Cred2	9.8	7.9	6.3	3.5	8.1
Cred3	11.5	9.5	8.1	3.3	10.1
Cred4	13.1	11.4	10.6	2.4	12.1
Worst	14.9	14.0	13.9	1.0	14.4
W-B	7.7	8.5	10.1	-2.4	9.3
t-stat	*49.0*	*84.4*	*83.6*	*27.5*	*92.5*

Panel D. Average Number of Observations

	Value	Neut	Growth	V-G	Full
Best	46.9	62.2	46.6	-0.3	151.9
Cred2	38.0	46.2	34.9	-3.1	143.7
Cred3	41.0	49.6	37.3	-3.6	124.9
Cred4	45.1	52.8	41.0	-4.1	136.9
Worst	40.7	63.8	62.5	21.9	189.2
W-B	-6.3	1.6	15.9	22.2	37.2
t-stat	*-5.21*	*0.71*	*5.96*	*9.17*	*6.53*

Table 6. O-Score, Leverage, and Aggregate Volatility Risk

The table presents the Carhart alphas, the Carhart+V alphas (from the Carhart model augmented with FVIX), and FVIX betas of the portfolios double-sorted on leverage and O-score. The sorts on leverage first create a separate group of zero-leverage firms, and then sort the rest of the firms on leverage into bottom 30%, middle 40%, top 30%. Then O-score quintiles are formed separately within each leverage group. FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2016. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Panel A. Carhart alphas

	Zero Lev	Low Lev	Medium	High Lev	Z-H
Low	0.294	0.191	0.276	0.266	0.028
t-stat	*2.58*	*2.61*	*4.64*	*3.40*	*0.21*
O2	0.239	0.177	0.138	0.204	0.035
t-stat	*2.60*	*2.61*	*2.30*	*2.54*	*0.27*
O3	0.357	0.225	0.170	0.145	0.212
t-stat	*3.24*	*2.92*	*2.65*	*1.79*	*1.55*
O4	0.292	0.037	0.103	-0.064	0.356
t-stat	*2.81*	*0.44*	*1.72*	*-0.61*	*2.26*
High	0.315	-0.232	-0.267	-0.216	0.531
t-stat	*1.97*	*-1.68*	*-2.78*	*-1.63*	*2.45*
L-H	-0.021	0.423	0.543	0.482	0.503
t(L-H)	*-0.12*	*2.81*	*4.55*	*3.16*	*2.19*

Panel B. Carhart+V alphas

	Zero Lev	Low Lev	Medium	High Lev	Z-H
Low	0.284	0.224	0.155	0.199	0.085
t-stat	*1.90*	*2.53*	*1.71*	*1.59*	*0.42*
O2	0.290	0.134	0.085	0.288	0.002
t-stat	*2.36*	*1.50*	*0.98*	*1.95*	*0.01*
O3	0.439	0.166	0.110	0.129	0.310
t-stat	*3.32*	*1.94*	*1.10*	*0.99*	*1.52*
O4	0.305	0.086	0.098	0.012	0.294
t-stat	*1.87*	*0.97*	*1.10*	*0.07*	*1.18*
High	0.156	0.012	-0.016	-0.036	0.192
t-stat	*1.02*	*0.11*	*-0.15*	*-0.22*	*0.77*
L-H	0.127	0.212	0.170	0.235	0.107
t(L-H)	*0.60*	*1.54*	*1.45*	*1.29*	*0.39*

Panel C. FVIX Betas

	Zero Lev	Low Lev	Medium	High Lev	Z-H
Low	0.142	0.069	-0.137	-0.272	0.414
t-stat	*1.39*	*0.76*	*-1.46*	*-2.86*	*3.21*
O2	0.122	0.042	-0.055	-0.160	0.282
t-stat	*1.37*	*0.64*	*-0.33*	*-1.19*	*2.10*
O3	0.127	0.118	-0.113	0.046	0.081
t-stat	*1.10*	*1.44*	*-1.15*	*0.34*	*0.42*
O4	0.246	0.554	-0.064	0.123	0.122
t-stat	*2.13*	*5.06*	*-0.65*	*0.82*	*0.64*
High	0.301	0.488	0.361	0.456	-0.154
t-stat	*1.97*	*3.48*	*2.98*	*2.27*	*-0.56*
L-H	-0.159	-0.419	-0.498	-0.728	-0.568
t(L-H)	*-1.01*	*-2.55*	*-4.03*	*-3.80*	*-2.12*