The Bright Side of Distress Risk†

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Abstract

Distressed firms tend to earn positive abnormal returns when aggregate volatility unexpectedly increases. This hedging property of distressed firms suggests a potential explanation for the puzzling negative relation between firm-specific distress risk and future alphas from benchmark asset-pricing models. Adding volatility risk factor to standard asset-pricing models reduces the alphas of the healthy-minus-distressed strategy by 80–95% and makes the slope on credit risk 45–95% smaller in cross-sectional regressions. Controlling for volatility risk exposure also contributes to explaining why the negative relation is stronger for volatile firms and growth firms.

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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 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 firm-level distress risk have lower, not higher risk-adjusted returns. Dichev (1998) finds that firms with a higher O-score and lower Z-score[1] have significantly lower future alphas. Avramov et al. (2009a) find negative alphas for firms with bad credit ratings, and Campbell et al. (2008) show similar evidence using their own default-predicting regression. This collective evidence is henceforth referred to as the distress risk puzzle.

The main economic mechanism in the paper that suggests a potential explanation of the distress risk puzzle is based on that levered equity can be viewed as a call option on the firm's assets. 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.[2] I conclude therefore that, holding everything else equal, the prices of distressed firms will decrease less than what the

[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.

[2]This mechanism 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 the online Theory Appendix.

CAPM and other factor models predict when both aggregate volatility and firm-specific uncertainty/idiosyncratic volatility increase in recessions. The empirical prediction is that distressed firms will be hedges against aggregate volatility risk.

This is not to say that simply buying distressed firms can offer a protection against recessions. Their equity is a highly levered claim on their assets, and therefore their betas are likely to be high. Also, distressed firms will be vulnerable to recessions for 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 the equity of distressed firms. This is the reason why alphas of distressed firms are 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, which causes their expected returns to appear too low.[3]

The second economic channel in the paper is based on the argument that extends the model in Johnson (2004). Johnson (2004) also 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) indicates 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. Thus, distressed firms with high uncertainty would have low systematic risk, and this risk can be lower than that of healthy firms with low uncertainty.

While the Johnson (2004) 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 the Johnson model are both true, distressed firms with high uncertainty should have low betas and zero alphas.

[3]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.

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 (IVol) and analyst disagreement increase in recessions together with market volatility. As the Johnson (2004) model shows, higher disagreement implies lower beta, and lower beta in recessions means lower risk in the Conditional CAPM sense and smaller losses in recession due to a smaller increase in future risk/discount rate.

A good example of how distressed firms react to volatility increases is the performance of firms in the bottom credit rating quintile (B+ and below on the S&P scale) in 2008–2009, a period of multiple upward spikes in aggregate volatility. In 2008–2009, average realized return to both distressed firms and the market portfolio was -70 bp per month. In the full sample, the market beta of the bottom credit rating quintile is 1.69, indicating 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 historically volatile period of 2008–2009 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 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 put forth 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 one reason why distressed firms have negative CAPM alphas is that they are hedges against 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 volatility risk factor is a superior asset pricing model that on average prices all anomalies better than other models.

The main part of the empirical analysis uses an aggregate volatility risk factor I call FVIXT. The FVIXT factor is a fully tradable 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. By construction, FVIXT posts good returns when VIX goes up, and thus a negative loading on FVIXT means exposure to aggregate volatility risk.

In portfolio sorts, adding FVIXT to the CAPM or the Carhart model reduces the negative alphas of the worst credit rating quintile and the positive alphas of the healthy-minus-distressed (HMD) strategy by 80–95%. In Brennan et al. (1998) cross-sectional regressions, with risk-adjusted returns as the dependent variable, adjusting for FVIXT exposure reduces the slope on the credit rating variable by 45–95%.

I test the robustness of my conjecture that a market-neutral position in distressed firms can be a hedge against volatility increases by looking at small subsamples (20-50 months) of “bad times”, such as NBER recessions, top 5-20% of VIX changes, market downturns of -3% to -6% per month. In the “bad times” subsamples, point estimates of distress firms CAPM alphas are uniformly positive and similar CAPM alphas of the HMD strategy are almost always negative, but the vast majority of the alphas lacks statistical significance despite their large economic magnitude (1–2% per month).

My explanation of the distress risk puzzle also produces several cross-sectional implications. Similar to the Johnson (2004) model, I predict that distressed firms with high firm-specific uncertainty/IVol have low expected returns;[4] my contribution is the additional prediction that such firms have the most positive FVIXT betas. I find in the data that controlling for FVIXT reduces the negative alphas of high-IVol distressed firms by roughly 75%.

I also 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 causes it to load positively on FVIXT. If the assets are themselves growth options, the option-likeness is even stronger, and therefore distressed growth firms will load most positively on FVIXT and have the most negative CAPM alphas. Hence, I provide a potential risk-based 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 – 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 partly explain that.

Lastly, consistent with the Johnson model, in which firm-specific uncertainty works through leverage to decrease systematic risk of levered firms, I find that sorting zero-leverage firms on O-score does not create a spread in alphas. An additional prediction generated by the aggregate volatility risk explanation of the distress risk puzzle is that the exposure of the HMD strategy to aggregate volatility risk is higher if the strategy is formed using highly levered firms. Controlling for the difference in aggregate volatility risk exposure, the difference in the alphas of HMD between zero-leverage and highly levered firms declines from 50 bp per month to -12 bp per month.

The rest of the paper proceeds as follows. Section 2 provides a review of the literature, Section 3 discusses data sources, while Section 4 performs preliminary tests. Section 5 presents evidence that volatility risk can be a potential explanation of a significant part of the distress risk puzzle. Section 6 looks at the relation between the distress risk puz-

[4] This prediction was tested in Chen et al. (2010) for O-score and Z-score and in Avramov et al. (2009b) for credit risk.

zle and firm-specific uncertainty, market-to-book, and leverage and shows that aggregate volatility risk contributes to explaining the cross-section of the distress risk puzzle. Section 7 summarizes robustness tests that are discussed in more detail in an online Robustness Appendix.[5]

2 Literature Review

The negative relation between default probability and expected returns appears so obviously backward that prevalent explanations 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 investors' failure to fully acknowledge potentially devastating effects of future downgrades.

Several papers propose rational explanations of the distress risk puzzle by suggesting that risk of distressed firms is mismeasured by existing asset pricing models. 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, and thus sorting on default probability will create an inverse sort on default risk.

What is missing from the existing risk-based explanations of the distress risk puzzle is the ultimate evidence that if one measures risk of distressed firms correctly, their alphas disappear. I fill this void by showing that the alphas decline by 80–95% 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

[5] Available at https://www.dropbox.com/scl/fi/7ar3c85xmmgbauy91eh56/Robustness-blind.pdf?rlkey=0ah2ol0l7vdbi0ldnt5vycuhj&dl=0.

different from those in Garlappi et al. (2008) and George and Hwang (2010), it is not mutually exclusive with respect to either of them.

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 (HMD) 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 a conclusion is premature: the HMD 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 increases. The point of this paper is that the HMD 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.[6]

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 say 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.[7]

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 theory, however, takes several additional steps 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 the ICAPM instead of the CCAPM. Third, it generates cross-sectional

[6]2008–2009 is a good example: the cumulative return to the HMD portfolio was -10.8%, while the cumulative return to the market portfolio was -20.1%. As a negative-beta asset, the HMD portfolio should have had large 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.

[7]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. My Panel C of Table 3 below pegs the distress risk puzzle in the CCAPM at 58 bp to 76 bp per month, close to Table 3 in O'Doherty (2012).

predictions about the distress risk puzzle and its volatility risk explanation (see Tables 4 and 5). Fourth, in Table 3, the ICAPM works better than the CCAPM and makes the distress risk puzzle insignificant.

Eisdorfer and Misirli (2020) find that the HMD strategy works only in bull markets, but breaks down in bear markets. This finding is consistent with my evidence that distressed firms do abnormally well when expected market 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). An alternative view is that my explanation of the distress risk puzzle and McQuade's theory focus on different components of volatility. The model in McQuade (2018) is solved using asymptotic expansions, so taking the model literally, it indicates 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 appears to be short-run volatility.

In Section 7.3, I split volatility into short-run and long-run components using Component GARCH as in Adrian and Rosenberg (2008) and find that FVIXT overlaps with short-run market volatility, but long-run market volatility helps healthy rather than distressed firms. This evidence also suggests that FVIXT 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, 2023, Barinov, 2012, 2013, 2018) that FVIXT 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 IVol and expected returns (from Ang et al., 2006), and the maximum effect of Bali et al. (2011). While the economic mechanism in my paper and in the prior papers is similar (option-like stocks are a hedge against volatility risk), I focus on the option-likeness created by leverage, while other papers look at growth options. In the data, leverage and growth options are negatively related, so the evidence in previous work that volatile growth firms load positively on FVIXT works against my finding the link between distress 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%, while controlling for FVIXT subsumes 50–100% of the distress risk puzzle and makes it 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 the 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 the Compustat annual file. The detailed description of O-score and EDF is in the online Data Appendix,[8] which also includes definitions of all 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 the online Robustness Appendix shows, the results are robust to using CRSP breakpoints and/or including stocks priced below $5 in 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

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

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

$$\begin{aligned} \Delta VIX_t &= \gamma_0 + \gamma_1 \cdot (VIX1_t - RF_t) + \gamma_2 \cdot (VIX2_t - RF_t) + \gamma_3 \cdot (VIX3_t - RF_t) \\ &\quad + \gamma_4 \cdot (VIX4_t - RF_t) + \gamma_5 \cdot (VIX5_t - RF_t) \end{aligned} \tag{1}$$

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 intercept, γ_0, is my aggregate volatility risk factor (FVIXT factor).

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 order to eliminate all look-ahead bias concerns, I construct a fully tradable FVIXT using an expanding-window regression. I exclude 1986–1987 to avoid the disproportionate effect of the October 19, 1987 outlier in the early years of the sample, use 1988–1990 as the learning sample and continue adding new data as time goes by. That is, the return to FVIXT in January 1991 is the weights (slopes) obtained from the factor-mimicking regression (1) using data from January 1988 to December 1990 times the returns to the base assets in January 1991, the return to FVIX in February 1991 is the weights estimated in January 1988 to January 1991 times the returns to the base assets in February 1991, and so on.

Idiosyncratic volatility is the standard deviation of residuals from the Fama-French (1993) model, fitted to the daily data for each firm-month (at least 15 valid observations are required)

The sample in the paper starts in January 1991 (due to availability of the VIX index and the need for a learning sample when forming a fully tradable FVIXT) and ends in December 2016 (due to availability of Compustat data on credit ratings).

4 Preliminary Tests

4.1 Descriptive Statistics

Panels A-D of Table 1 perform quintile sorts on credit rating and report 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 a 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.[9]

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 hold up using other distress measures (Section 1 of the online Robustness Appendix[10] provides further evidence).

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 (2004) model, distressed firms are riskier than healthy firms holding firm-specific uncertainty fixed. Higher firm-specific uncertainty makes the risk of distressed firms lower; hence, if

[9]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.

[10]The Robustness Appendix is available at https://www.dropbox.com/scl/fi/7ar3c85xmmgbauy91eh56/Robustness-blind.pdf?rlkey=0ah2ol0l7vdbi0ldnt5vycuhj&dl=0.

distressed firms have sufficiently high firm-specific uncertainty, their risk can become lower than that of healthy firms.

In Panel B of Table 1, I find that as one goes from firms with the best to the worst credit rating, IVol doubles, variability of earnings and cash flows quadruples, and analyst disagreement and analyst forecast error increase by a factor of five. Thus, firms with bad credit ratings are exactly 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.[11]

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, the "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 the "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 directly at the positive effect of increases in 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 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 direct evidence of the main mechanism at work in my paper.

[11] In the 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.

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 IVol increases. Unless the IVol of volatile distressed firms reacts less to VIX changes than the IVol 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 IVol of individual firms on changes in VIX and report the average slopes in each credit rating quintile. The slopes increase monotonically and in ultimately more than double going from best to worst credit rating quintiles, confirming my hypothesis that the volatility of distressed firms 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 IVol to VIX changes is flat across credit rating quintiles. In other words, the first row shows that the 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 rows repeat rows one and two using analyst disagreement instead of IVol and find an even stronger relation between credit rating and responsiveness of firm-level analyst disagreement to changes in VIX – the slopes increase tenfold and sixfold, respectively, from best to worst credit rating quintiles.[12]

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 IVol is significantly correlated with market

[12] Barinov (2017) also performs sorts on IVol 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.

volatility, and both tend to increase during recessions. Section 8 in the online Robustness Appendix presents further evidence.

4.3 FVIXT as an Aggregate Volatility Risk Factor

In the rest of the paper, in formal asset pricing tests of the aggregate volatility explanation of the distress risk puzzle, I use the FVIXT factor, a version of 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 to explain several important anomalies, including the IVol discount of Ang et al. (2006) (see Barinov and Chabakauri, 2023), the analyst disagreement effect of Diether, Malloy, and Scherbina (2002) (see Barinov, 2013), and the new issues puzzle (see Barinov, 2012).[13]

In order to be a valid and useful ICAPM factor, the FVIXT factor has to satisfy three requirements. First, it has to be significantly correlated with the variable it mimics (the change in VIX). In untabulated results, I find that the correlation between FVIXT returns and VIX changes is expectedly high at 0.738 and conclude that FVIXT clears the first hurdle of being a good mimicking portfolio.

Second, FVIXT has to earn a sizeable and statistically significant risk premium, both in raw returns and, most importantly, on the risk-adjusted basis. Since FVIXT is, by construction, positively correlated with VIX changes, FVIXT represents an insurance against increases in aggregate volatility, and, as such, has to earn a negative risk premium. Panel C of Table 2 shows that the average raw return to FVIXT is -1.14 per month, t-statistic -4.71, while the CAPM alpha and the three-factor Fama and French (1993) alpha of FVIXT are both at about -38 bp per month, t-statistics -4.66 and -4.29, respectively. The Carhart (1997) alpha of FVIX is at -40.4 bp per month, and even the six-factor alpha (the five factors from Fama and French (2015) plus momentum) is at -31.7 bp per month, t-statistic -4.16.

I conclude that FVIXT captures important risk investors care about – the negative

[13]Barinov (2012, 2013) and Barinov and Chabakauri (2023) use a version of FVIX that employs a full-sample factor-mimicking regression, while FVIXT uses only information available to the econometrician at a certain date; Section 4.2 of the online Robustness Appendix to this paper shows that the correlation between FVIX and FVIXT is 0.991 and their risk premia are within 10 bp of each other.

alphas suggest investors are willing to pay a significant amount for insurance against this risk provided by FVIXT. Hence, FVIXT clears the second hurdle for being a valid ICAPM factor.[14]

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

The rest of Table 2 looks into the base assets for FVIX, quintile portfolios formed based on historical sensitivity to VIX changes. Panel A tabulates several important firm characteristics across the quintiles and finds that VIX sensitivity is largely unrelated to firm characteristics behind Fama-French factors and is also unrelated to leverage and Z-score. The relation between VIX sensitivity and size is hill-shaped: firms with both large positive and large negative VIX sensitivity tend to be smaller, while firms with weaker VIX sensitivity are larger. I also observe a U-shaped relation between VIX sensitivity and O-score/credit rating: firms in the extreme VIX sensitivity quintiles look a bit more distressed than firms in the middle quintiles, though the difference is not large (2-3 notches in terms of credit rating, which is comparable to differences in credit rating between adjacent credit rating quintiles). The main conclusion from Panel A is that I observe no particular concentration of a certain kind of firms (distressed firms, value firms, unprofitable firms) in any VIX sensitivity quintile, so FVIX cannot mechanically explain the distress risk puzzle by loading up on a single quintile where, for example, distressed firms would be concentrated.

Panel B reports, in its first row, the average loadings on the VIX sensitivity quintiles from the factor-mimicking regressions that create FVIX.[15] Consistent with strong negative correlation between VIX change and market return, the coefficients are primarily nega-

[14]In Section 4.4 in the online Robustness Appendix, I compare my FVIXT with the original FVIX from Ang et al. (2006). Ang et al. run the factor-mimicking regression separately for each month, and therefore their FVIX is a noisier version of FVIXT. While the correlation between the two is 0.78, the alphas of the original FVIX are one-third smaller and statistically insignificant primarily because of a much larger standard error.

[15]As Section 3 describes, the factor-mimicking regression is performed each month using expanding window.

tive (one has to short most stocks to create a portfolio that tracks VIX changes). The coefficients also increase from quintile two to quintile five (one tends to short more the portfolios that react more negatively to VIX increases in order to create a portfolio that gains when VIX goes up); the relatively small negative slope on quintile one is probably due to noise in returns of small firms that populate the extreme VIX sensitivity quintiles.

The second and fourth rows of Panel B report average returns and alphas of VIX sensitivity quintiles. Both the average returns and the CAPM alphas decline monotonically and significantly with VIX sensitivity, confirming that VIX sensitivity is negatively priced, as was first found by Ang et al. (2006). The third row of Panel B reports average products of returns to VIX sensitivity quintiles and the loadings on these quintiles from the factor-mimicking regression. The third row helps to gauge which quintile contributes more to the negative average return of FVIX. The conclusion from the third row is that the second and third quintiles are the main contributors (again, those quintiles are not populated by distressed or levered firms, so FVIX is unlikely to mechanically explain the distress risk puzzle).

5 Distress Risk Puzzle and Aggregate Volatility Risk

5.1 Distress Risk Puzzle in Portfolio Sorts

Table 3 performs quintile sorts on credit rating and reports alphas from several factor models before and after augmenting them with the FVIXT factor. Table 3 also reports FVIXT betas; other betas are not reported to save space. The credit rating portfolios are rebalanced each month; I skip a month between portfolio formation and return calculation to eliminate any microstructure effects or 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 (A1 and B1) use the CAPM as the benchmark model and estimate the distress risk puzzle (defined as the alpha of the HMD portfolio) at 99 bp (72 bp) per month in value-weighted (equal-weighted) returns. Value-weighted alphas present familiar

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

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 both from the long and short sides.

Most importantly, the top two panels of Table 3 reveal that the two-factor ICAPM with the market factor and FVIXT can explain a large part of alphas in all credit rating quintiles and reduce the HMD alpha differential to insignificance. The driving force is FVIXT 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 FVIXT betas across credit rating quintiles is also monotonic and significant.

The next two panels (A2 and B2) use the Carhart (1997) model as the benchmark. Controlling for the fact that distressed 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 roughly 64 bp per month in both value-weighted and equal-weighted returns, lower than the CAPM estimates, but still economically and statistically significant. The explanatory power of FVIXT and the FVIXT beta spread between healthy and distressed firms remain large and significant in the Carhart model: after I control for FVIXT, alphas of the worst credit rating quintile are within 3.5 bp of zero, their differences with alphas of the best credit rating quintile are within 5.5 bp of zero, and the FVIXT beta differential between healthy and distressed firms has t-statistics exceeding 3.9.[17]

To sum up, Panels A1-A2 and B1-B2 of Table 3 present the main result of the paper that controlling for the FVIXT factor reduces the estimates of the distress risk puzzle by 80–95% and that distressed firms appear to be hedges against aggregate volatility risk.[18]

[17]In untabulated results, I sort firms into credit rating deciles, which produces a larger and more significant spread in CAPM/Carhart alphas, but does not impact the ability of FVIXT to reduce the alpha spread.

[18]Section 1 of the online Robustness Appendix uses other three popular distress measures – O-score from Ohlson (1980); failure probability from Campbell et al. (2008); expected default frequency (EDF) based on Merton (1974) as estimated by Bharath and Shumway (2008). Results reveal that all three measures are strongly positively related to FVIXT betas, as expected. Controlling for FVIXT reduces

In untabulated results, I add the Pastor and Stambaugh (2003) liquidity factor and/or a factor based on the Jegadeesh (1990) short-term reversal to the Carhart model and arrive 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 Fama and French (2015) model. The five-factor model generates a smaller HMD alpha than the Carhart model. Further analysis reveals that FVIXT explains the alpha of RMW, but RMW cannot explain the alpha of FVIXT, suggesting that aggregate volatility can be the state variable behind RMW (Barinov, 2023, presents detailed analysis of this hypothesis). Adding FVIXT to the five-factor Fama-French model reduces the spread in both RMW and FVIXT betas between healthy and distressed firms, but leaves both beta spreads significant.

5.2 Distress Risk Puzzle in the Conditional CAPM

Panels A3 and B3 of Table 3 demonstrate the existence of the second channel that links the distress risk puzzle and aggregate volatility risk. The second channel predicts procyclical market betas of distressed firms. Panels A3 and B3 of Table 3 present the Conditional CAPM estimates that are completely free of look-ahead bias and use the standard four conditioning variables: default premium (DEF), dividend yield (DIV), Treasury bill yield (TB), and term spread (TERM). I start with the learning sample of seven years, 1986–1992, to estimate the Conditional CAPM for each credit rating quintile. In January 1993, I assign the alpha from the 1986–1992 sample to each quintile portfolio. I then use the conditional beta equation with coefficients from the 1986–1992 sample and plug in the December 1992 values of the four business cycle variables (DEF, DIV, TB, TERM) to

the distress risk puzzle based on the alternative distress measures by 25–35 bp per month depending on the baseline model used (CAPM/Carhart), which, on average, constitutes about 70% of its original value. A similar reduction is observed for the negative alpha of the most distressed quintile, which creates the majority of the distress risk puzzle.

[19] In Section 10 of the online Robustness Appendix, I include stocks priced below $5 back into the sample, since low-price stocks are more likely to be distressed and dropping them can potentially weaken the distress risk puzzle. I find 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 HMD portfolio changes from 72 to 84 bp per month. The FVIX beta of that portfolio changes accordingly though, and the ICAPM alpha changes from 15 bp in Panel A of Table 3 to -6 bp in the results with stocks priced below $5 included.

estimate conditional beta of each portfolio in January 1993. Then, I add January 1993 to the estimation period and re-estimate the Conditional CAPM in the January 1986 to January 1993 sample. In February 1993, I assign the alpha from the January 1986 to January 1993 sample to each quintile portfolio and use the conditional beta equation with coefficients from the January 1986 to January 1993 sample, plugging in January 1993 values of DEF, DIV, TB, TERM to estimate the conditional beta of each portfolio in February 1993, and proceed likewise for subsequent months.

The first two rows of Panels A3 and B3 tabulate static CAPM and Conditional CAPM alphas. In value-weighted returns, I observe that the alpha of the healthy-minus-distressed (HMD) strategy (B-W column) declines by 40 bp per month (from 98 to 58 bp per month) after the market beta is made time-varying. The decline comes 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 that presented by O'Doherty (2012): the Conditional CAPM contributes to explaining the distress risk puzzle, but leaves a large fraction of it unexplained, making necessary the use of an additional risk factor, FVIXT.[20]

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 in recessions vs. expansions (row four).[21] In value-weighted returns, I observe a large shift in the conditional beta of the HMD strategy, which increases by 0.43 during recessions

[20] The statistical significance of Conditional CAPM alphas in Panels A3 and B3 is exaggerated, because the alphas in, say, January 1993 and February 1993, are calculated from almost the same data (January 1986 to December 1992 sample and January 1986 to January 1993 sample, respectively. That makes the alpha series very autocorrelated and inflates the t-statistic of average alpha. Section 9.3.1 and Table 16A present more conventional full-sample estimates of the Conditional CAPM, which yield similar alphas with much smaller t-statistics.)

[21] The definition of expansions and recessions in Panels A3 and B3 follows the tradition in the Conditional CAPM literature (see, e.g., Petkova and Zhang, 2005): 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). To eliminate look-ahead bias, the predictive regression (of MKT-RF on DEF, DIV, TB, and TERM) is estimated using an expanding window: I use 1983–1992 as the learning sample, perform out-of-sample forecast one month ahead, and then add that month to the estimation sample and perform an out-of-sample forecast for the next month. Expansion is defined as months when the out-of-sample forecast falls below the in-sample median.

– primarily because the conditional beta of the worst credit rating quintile decreases in recessions by 0.37, supporting the prediction that market betas of volatile distressed firms are procyclical.[22]

In equal-weighted returns, the difference in betas between expansions and recessions is largely flat across all credit rating quintiles but the one with the worst credit rating, 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 evidence that option-likeness increases sharply in the worst credit rating quintiles, and in the other quintiles it largely stays flat). In the worst credit rating quintile, the recessions vs. expansion difference in market betas takes a sharp and marginally significant dip, consistent with my prediction.[23]

5.3 Distress Risk Puzzle in Cross-Sectional Regressions

Table 4 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 4 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 FVIXT, 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

[22]In Section 9.3.4 of the online Robustness Appendix, I also make the alpha conditional on the same four conditioning variables. The conditioning variables come out jointly significant, and I also find that the Conditional CAPM alpha of distressed firms becomes positive in recessions, and the HMD alpha differential becomes negative in recessions. Both pieces of evidence corroborate my finding that the Conditional CAPM cannot explain the alphas in the credit rating sorts: if it could, the Conditional CAPM alpha of all quintiles, including the distressed firms quintile, would be zero and thus independent of the business cycle.

[23]In Section 9.3.2 of the 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 a full 60 bp per month. FVIX betas of distressed firms or the HMD 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 3. I have also experimented with making FVIX beta conditional and found a moderate effect on the ICAPM alphas, around 10 bp per month on average.

abnormal return in month t is the raw return less the sum of the products of these betas with factor returns in month t.[24] My hypothesis is that my main variable, credit rating, will be significant in all regressions, in which the risk-adjustment does not include FVIXT, and will lose significance once the risk-adjustment includes FVIXT.

Columns two, four, six, and eight of Table 4 confirm the result in Table 3 that the distress risk puzzle is equally strong and significant in CAPM, Fama-French three-factor and five-factor, and Carhart alphas. 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.[25] 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 $7.34 \cdot 9 = 65$ bp per month, which is close to the spread in CAPM alphas in Table 3.

When I add FVIXT to either the CAPM (column three) or the five-factor Fama and French (2015) model (column nine), the slope on credit rating decreases by at least 90% and its t-statistic drops below 0.2. In columns five and seven, where FVIXT is added to the three-factor Fama and French (1993) model and the Carhart (1997) model, the decline in the credit rating slope is smaller, at roughly 50%, and the slope remains marginally significant at the 10% level. This smaller decline is likely due to the overlap between HML and FVIXT: as Barinov and Chabakauri (2023) show, FVIXT can partly explain the value effect.

It is also of interest that controlling for FVIXT makes the slope on the momentum variable visibly smaller. This is somewhat at odds with Table 3, where I find little overlap between FVIXT and the momentum factor, but suggests that one reason why recent losers have low returns is that they become distressed and turn into hedges against aggregate volatility risk.

[24] In addition to different risk-adjustments on the left-hand side, all regressions in Table 4 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.

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

5.4 Distressed Firms in Bad Periods of Time

The main prediction of this paper is that aggregate volatility risk can be a potential explanation of the distress risk puzzle, which implies that firms with a bad credit rating tend to perform relatively well in response to unexpected increases in aggregate volatility, which I proxy by changes in the VIX index. The positive loadings of distressed firms on FVIXT (see Table 3) imply exactly that, since FVIXT closely tracks VIX changes by construction.

This subsection provides corroborating evidence by looking directly at CAPM alphas of distressed firms and alphas of the HMD strategy in different subsamples that are likely to be classified as "bad times". The hypothesis is that distressed firms will have positive CAPM alphas in "bad times" and the HMD strategy will have negative alphas.

Panel A of Table 5 uses values of VIX to create "bad times" subsamples to address the concern that some months with VIX increases (and positive FVIX returns) may not be "bad months" if the initial value of VIX is low enough. The first row of Panel A looks at months with VIX in the top 5% (19 such months in my 1986–2016 sample, with the value of VIX 35.4), the second row considers months with VIX in the top 10% (37 such months, VIX exceeds 29.56), etc. The sample sizes are small and thus power can be an issue.

Panel A1 shows that the HMD portfolio posts economically sizeable negative alphas in months with high VIX. In months when VIX tops the 95th (90th) percentile, the HMD portfolio has a -3.7% (-4.7%) per month value-weighted alpha with t-statistic -1.38 (-2.13). When VIX values are not as extreme, the negative alphas are expectedly smaller and statistically insignificant, but still economically large (-0.86% to -2.41%).[26]

The negative alphas of the HMD portfolio in Panel A are driven by positive alphas of distressed firms. In months when VIX tops the 95th (90th) percentile, distressed firms in Panel A1 post 3.85% (4.935%) alpha, significant at 10% (5%) level. In equal-weighted returns, the alphas of distressed firms in those months are economically large at 1.2% (2.4%) per month, though not statistically significant.[27]

[26] In equal-weighted returns (untabulated), the alphas are smaller and insignificant, but in a small sample equal-weighted returns can be affected by microstructure noise, a few outlier returns to small firms, etc.

[27] A look at correlations between firm-level CAPM alphas of credit rating quintiles and change in VIX

Alphas of other credit rating quintiles are generally unremarkable. Out of 20 such alphas reported in Panel A1, only two are significant at the 5% and one more is significant at the 10%, which is close to random variation. The alphas of other quintiles are positive, suggesting that firms with a credit rating do a bit better than average in tough times (and non-rated firms do a bit worse than average), but those alphas are usually insignificant and usually several times smaller than the alpha of the worst credit rating quintile, which is the only quintile alpha that stands out.

Panel A2 reports several characteristics of the VIX change subsamples, beyond the VIX change cut-off and the number of months in the subsample. For example, when VIX is in the top 5%, average excess market return (MKT-RF) is -3.88% and 11 months out of 19 subsample have negative excess market returns. When VIX is above the 85th percentile (i.e., VIX exceeds 26.63), average excess market return is -2.8% and 65% of those months (i.e., 37 out of 57 months) have negative excess market returns. The evidence in Panel A2 suggests that months with high VIX values are indeed "bad months" when bad news arrive.

Panels B and C of Table 5 look at more widely used measures of "bad times": market downturns and NBER recessions. I expect the results to be weaker compared to Panel A, since the economic mechanism in the paper works through volatility, and market returns and NBER recessions are imperfect proxies for volatility. On the other hand, recording good performance of distressed firms using more common measure of "bad times" provides extra evidence that distressed firms can be used to hedge consumption risk.

Panel B reports CAPM alphas of the HMD strategy and credit rating quintiles in the subsamples when the market excess return is below -3%, -4%, etc. When the market is down by more than 6% (the rightmost column of Panel B indicates that there are 21 such months in my sample), I find that the value-weighted (equal-weighted) average alpha of HMD is -4.3% (-1.96%) and that distressed firms have value-weighted (equal-weighted) average alpha of 1.2% (3.7%). The numbers are economically quite large, but statistically

provides similar evidence: in untabulated results, I find that they range from -0.26 for healthy firms to 0.2 for distressed firms. Similarly, partial correlations (conditional on market return) of quintile portfolio returns with FVIXT increase from -0.47 for the best credit rating quintile to 0.38 for the worst credit rating quintile.

insignificant because of the small sample size. Other subsamples of months with the market return below -5%, -4%, and -3% present similar evidence: the HMD strategy has large and negative CAPM alphas and distressed firms have large and positive CAPM alphas, though none of the alphas are statistically significant. Alphas of other credit rating quintiles are mostly positive, but always insignificant. The best credit rating quintile has slightly negative alphas in three subsamples out of four.

In Panel C, I first estimate the CAPM in NBER recessions and NBER expansions only, and then test the significance of the difference between the quintile alphas in expansions and recessions by running

$$R_t - RF_t = \alpha_{Exp} + \beta_{Exp} \cdot (MKT_t - RF_t) + \Delta\alpha_{R-E} \cdot REC_t + \Delta\beta_{R-E} \cdot REC_t \cdot (MKT_t - RF_t)\epsilon_t \tag{3}$$

where REC_t is the recession dummy (1 during NBER recession months, 0 otherwise) and $\Delta\alpha_{R-E}$ is the difference between alphas in recessions and expansions.

Since NBER expansions are much longer than NBER recessions (in my 1991-2016 sample, I have 312 months total and only 27 of them are marked as recessions), alphas in expansion look similar to alphas in the full sample. The alphas of two worst credit rating quintiles are significantly negative during expansions, and the alpha of the top credit rating quintile is 4-5 times smaller in absolute magnitude, but positive and close to significance at the 10% level.

For the two best credit rating quintiles, alphas during recessions are within 2.5 bp of alphas during expansions. On the other hand, alphas of the two worst credit rating quintiles are by more that 1% per month more positive in recessions than in expansions, consistent with my explanation of the distress risk puzzle. During recessions, the alphas of the two worst credit rating quintiles are positive 43-48 bp per month – however, they are statistically insignificant (as is their difference with alphas in recessions), because the sample of 27 months of NBER recessions is too small.

The alpha of the middle quintile during recessions is just 8-12 bp smaller than similar alphas of the worst rated firms, which is a bit surprising; however, in expansions the alpha of the middle quintile is also slightly positive, and the change of the middle quintile alpha from expansions to recessions is just 33 bp, three times smaller than a similar change for the worst rated quintiles, and this much smaller change is consistent with my explanation of the distress risk puzzle.

Panel D presents an additional way to judge whether HMD strategy underperforms the CAPM prediction when VIX increases and whether distressed firms outperform at the same time: I regress daily returns to HMD strategy/credit rating quintiles on daily market return and daily VIX change:

$$Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \gamma_{\Delta VIX} \cdot \Delta VIX_t \tag{4}$$

Similar to when I run the factor-mimicking regression, daily frequency is chosen here because at the daily frequency the autocorrelation of VIX is 0.967 (so change in VIX is very close to the true innovation/white noise), while at the monthly frequency the autocorrelation of VIX is only 0.833 (so monthly change in VIX has a significant mean-reverting component).

The top two rows of Panel D show that loadings of the HMD portfolio on change in VIX are negative and significant with t-statistics exceeding 7.5 by absolute magnitude. Likewise, a market-neutral position in distressed stocks would significantly gain in response to volatility increases, as evidenced by the positive loadings of those firms on change in VIX (with t-statistics exceeding 5).[28] The three middle quintiles also load positively on change in VIX, but those loadings are several times smaller than the loading of the worst credit rating quintile, consistent with my explanation of the distress risk puzzle and with FVIXT betas reported in Table 3. The best credit rating quintile loads negative and significantly on daily change in VIX, again consistent with FVIXT betas in Table 3 and those cells in Panels A and B that report negative CAPM alphas of the best credit rating quintile in bad times.

[28]A simple back-of-envelope calculation can shed light on the economic magnitude of the effect VIX change has on, for example, the value-weighted HMD portfolio. A pairwise regression of market returns on change in VIX produces the slope of -0.34, suggesting that a one-point increase in VIX leads to the market dropping by 34 bp. According to the CAPM, if VIX increases by 1 point and the market then drops by 34 bp, the value-weighed HMD portfolio, with its market beta of -0.682, should gain $-0.682 \cdot (-0.34\%) \simeq 0.232\%$. However, the loading on change in VIX suggests that it will gain 12.2 bp (or 53%) less than that, which seems to be an economically significant effect.

Lastly, in the bottom four rows of Panel D, I split the sample into NBER recessions (middle two rows) and NBER expansions (bottom two rows) to verify that distressed firms load positively on VIX changes not only during expansions that dominate my sample (more than 90% of months in my sample are NBER expansions), but also in recessions, when investors care about the positive loading. I do find that distressed firms load positively on VIX changes in recessions (and HMD loads negatively), and those loadings are three times larger than in expansions.

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 react in a more positive way to increases in firm-specific uncertainty, because their equity is similar to a call option on the assets. First, higher uncertainty about the assets means lower beta of equity. This effect leads to distressed firms having lower beta 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 the online Theory Appendix shows, both hedging channels above are likely to be stronger for distressed firms with high firm-specific uncertainty/volatility. The intuition is as follows: if a firm is not volatile and its volatility increases, the increase in volatility is unlikely to be large and therefore will have little effect on the value of its option-like equity.[29] Hence, the hedging power of distressed firms and therefore the distress risk puzzle should be stronger among firms with high firm-specific uncertainty/volatility, and aggregate volatility risk should be able to explain this pattern.

Table 6 performs double sorts, first on IVol (IVol) and then on credit rating.[30] IVol

[29]Panel D of Table 1 confirms that volatility of volatile firms increases more drastically if the average levels of firm-specific and aggregate volatility increase.

[30]The sorts are conditional due to a strong correlation between IVol and credit rating. In independent

is the standard deviation of residuals from the Fama-French (1993) model, fitted to the daily data for each firm-month (at least 15 valid observations are required). 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 IVol 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 the distress risk puzzle stronger for volatile firms, but favor a mispricing explanation.

Panels A2 and B2 look at the alphas of the double-sorted portfolios after FVIXT is added to the CAPM and Carhart model, respectively, and report two novel results. First, aggregate volatility risk is able to explain at least 50% of the distress risk puzzle in the highest IVol group, as well as a slightly smaller fraction of why the distress risk puzzle is stronger for high IVol firms. Second, FVIXT explains an equally large part of related concentration of the IVol effect of Ang et al. (2006) in the most distressed quintile (which is again consistent with my explanation of the distress risk puzzle).

Panels A3 and B3 look at FVIXT betas in the double sorts and corroborate the evidence in Panels A2 and B2. Indeed, the FVIXT beta of distressed firms is significantly more positive if these firms also have high IVol.[31] The large and positive FVIXT beta of firms with a bad credit rating and high IVol is also responsible for significantly more negative FVIXT betas of the HMD strategy in the high-IVol subsample and significantly more negative FVIXT betas of the low-minus-high IVol strategy in the distressed firms subsample (both of these strategies short bad credit rating, high-IVol firms with their large and positive FVIXT betas). Hence, FVIXT betas in Panels A3 and B3 confirm that FVIXT exposures contribute to explaining why the distress risk puzzle is stronger for high-IVol firms, just as my explanation of the distress risk puzzle would predict, and also contributes to explaining why the IVol effect is stronger for distressed firms, as follows from the same

sorts, many firms fall on the "main diagonal" and other corners, such as the portfolio of high-IVol firms with the best credit rating, often have a single-digit number of firms.

[31] In fact, in the two-factor ICAPM with the market and FVIXT, firms in the worst credit rating quintile only have positive FVIXT betas if those firms belong to the top IVol tercile.

economic mechanism.

Panel C of Table 6 tabulates average credit rating (coded as 1=AAA, 2=AA+, ... , 21=C, 22=D) in the double sorts and expectedly finds that higher IVol firms have worse credit rating – the difference in credit rating between low and high IVol groups is about 4 notches. However, the spread in credit rating between best and worst credit rating quintiles is the same in all three IVol 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 HMD spread in credit rating in the low IVol group is similar to the one-minus-four quintile spread from single sorts, while the similar HMD spread in the high IVol group is close to the two-minus-five quintile spread. Panel A1 of Table 3 estimates the respective alpha spreads at 58 bp and 67 bp per month, which suggests that the relation between IVol and the distress risk puzzle documented in Table 6 is unlikely to be mechanical.

Panel D of Table 6 records the average number of firms in the double sorts.[32] In unconditional sorts, firms would be concentrated along the main diagonal, but conditional sorts in Table 6 spread out the firms rather well, making all portfolios balanced.[33]

In Section 2.1 of the online Robustness Appendix, I redo Table 6 replacing IVol with another measure of firm-specific uncertainty: analyst disagreement. That limits my sample, but repeats the test in Avramov et al. (2009b). The results are similar to Table 6. The distress risk puzzle appears to be coming almost exclusively from high disagreement firms, among which it is between 55 and 87 bp per month, and controlling for FVIXT reduces the distress risk puzzle to 7-9 bp per month. 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. I add to that the new evidence that adding FVIXT to asset-pricing models reduces the estimate of the disagreement effect for distressed firms from 47-79 bp per month to 5-25 bp per month.

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

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

Section 9.2 of the online Robustness Appendix presents a more direct test of my additional prediction about conditional market betas of the HMD strategy during recessions and expansions in the high and low IVol/analyst disagreement subsamples. I find that one reason why in the high IVol/disagreement subsample the HMD strategy is riskier is that its market 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. They 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 them. Such firms have no pledgable assets and low chances to survive to a point in time when their bright future prospects are supposed to be realized.

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 suggests that option-like firms are hedges against aggregate volatility increases. Firms can be option-like if their equity is similar to 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 the most option-like firm and hence should be the best hedge against aggregate volatility risk, which can potentially 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. This can provide an alternative, risk-based explanation of their findings that the distress risk puzzle is driven primarily by growth firms, in particular by distressed growth firms.

Table 7 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, since my proposed mechanism behind the distress risk puzzle can also predict that growth firms will be hedges against aggregate volatility risk (see Barinov and Chabakauri, 2023, for 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 7 is a clean version of itself, purged of the confounding influence of the value effect.

In Panels A1 and B1 of Table 7 that report the CAPM and Carhart alphas, respectively, I observe that the distress risk puzzle does not exist in the value subsample and becomes the strongest 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 7 presents the test of my explanation of the distress risk puzzle. In Panels A2 and B2, I present alphas from the two-factor ICAPM with the market factor and FVIXT and from the Carhart model augmented with the FVIXT factor (Carhart+V). Consistent with my explanation of the distress risk puzzle, which provides an alternative to the mispricing argument in Griffin and Lemmon (2002), I observe that controlling for aggregate volatility risk reduces the distress risk puzzle in the growth subsample from 79-87 bp per month to 19-29 bp per month and also reduces the difference in the distress risk puzzle between growth and value subsamples from 64-68 bp per month to 24-41 bp per month. The large negative alphas of distressed growth firms sees a similar reduction from -40 and -51 bp in Panel A1 to just -6 and -7 bp per month.

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

Table 7 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 quintile with the worst credit rating, 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 the value-minus-growth strategy has a significant exposure to aggregate volatility risk only for the most distressed firms. This can explain why in Panels A2 and B2, which look at the alphas controlling for FVIXT, the value effect for the most distressed firms is reduced compared to Panels A1 and B1.

Panels C and D of Table 7 tabulate average credit rating and average number of firms in each of the 15 double-sorted portfolios. Portfolios appear balanced in terms of number of observations, with distressed growth and distressed neutral portfolios having more firms than other portfolios; the latter fact is largely caused by the use of NYSE breakpoints, which make the worst credit rating quintile the largest in single sorts as well.

Credit rating depends positively on market-to-book, especially among healthy firms. That leads to the HMD spread in credit rating to be 2–3 notches larger in the growth firms subsample. On the other hand, the average credit rating of the most distressed firms is roughly the same in the value and growth firms subsamples, and since the distress risk puzzle is primarily coming from the short side, the difference in the HMD 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 the online Robustness Appendix, I repeat the analysis in Table 7 replacing credit rating with O-score, which allows for an easier comparison with Griffin and Lemmon (2002), who also perform double sorts on O-score and market-to-book. The results are very similar to Table 7, indicating that the relation between the distress risk puzzle and market-to-book and its aggregate volatility risk explanation does not depend on which measure of distress one uses.

6.3 Distress Risk Puzzle and Leverage

The existence of risky debt makes the firm's equity option-like and therefore turns it into a hedge against aggregate volatility increases. Zero-leverage firms can also become distressed and go out of business, but distress will not turn zero-leverage firms into hedges against aggregate volatility risk.

More than 95% of firms that have a credit rating also have debt, but distress measures such as O-score can be computed for any firm, including a zero-leverage one. Many studies of the distress risk puzzle starting with Dichev (1998) sort firms on O-score and include zero-leverage firms in their sample.

Table 8 sorts firms on leverage and then, within each leverage group, into O-score quintiles. I sort zero-leverage firms into a separate group and positive-leverage firms into the 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 FVIXT betas.[34] For firms with nonzero 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 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 FVIXT 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 HMD alpha spread in the zero-leverage group, which is significantly different from the similar HMD spread of 48 bp per month in the top leverage group. In the other two leverage groups, the distress risk puzzle is close to that of the top leverage group.

Panel C reports FVIXT betas from the Carhart model augmented with FVIXT (Carhart+V in the table) and finds that the betas align with the Carhart alphas in Panel A. In particular, the FVIXT beta of the HMD portfolio in the zero-leverage group is -0.159, t-statistic

[34] 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 the firm value of zero-leverage firms depending on O-score.

-1.01, as compared to the FVIXT betas of similar HMD 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 FVIXT to the Carhart model reduces the distress risk puzzle estimate for the highly levered firms from 48 bp to - 5 bp per month and similarly reduces the difference in the distress risk puzzle between highly levered and zero-leverage firms from 50 bp to -11 bp per month.

I conclude that sorting on O-score in the zero-leverage subsample creates no distress risk puzzle and no spread in FVIXT betas, as my explanation of the distress risk puzzle would predict. In contrast, sorting levered firms on O-score produces a significantly greater distress risk puzzle and spread in FVIXT betas, and the latter spread appears to be positively related to leverage.[35]

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 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 the online Robustness Appendix,[36] I find that the disappearance of the distress risk puzzle when the time around downgrade is removed can be attributed to look-ahead bias. First, I show that the distress risk puzzle is restored if the six months after downgrade are not removed. Second, I find that the relation between credit rating

[35]Section 7 of the online 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. The Robustness Appendix finds, however, that the relation between operating leverage and distress is not strong and that operating leverage is not related to FVIXT betas. Thus, operating leverage is unlikely to have a confounding effect on the results in Table 8.

[36]Available at https://www.dropbox.com/scl/fi/7ar3c85xmmgbauy91eh56/Robustness-blind.pdf?rlkey=0ah2ol0l7vdbi0ldnt5vycuhj&dl=0.

and FVIXT betas is intact even if months around the downgrade are removed. The main argument in Avramov et al. 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 FVIXT 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 Alternative FVIXT Versions

The baseline FVIXT used in the paper uses, as base assets, quintile portfolios pre-sorted on historical return sensitivity to VIX changes. In Section 4.1 of the 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 FVIXT at about -50 bp per month. The alpha of FVIX6 is smaller at roughly -30 bp per month. FVIX6 and FVIXind betas of the HMD portfolio are always significantly negative and more negative in growth and high-IVol subsamples than in value and IVol subsamples. FVIX6 betas are very similar in magnitude to FVIXT betas, while FVIXind betas are roughly 30% smaller. Consistent with that, the ICAPM alphas of the HMD strategy are almost always insignificant when I use FVIX6 or FVIXind instead of the baseline FVIXT, though the ability of FVIX6 or FVIXind to explain the CAPM alpha is roughly 25–30% smaller than that of FVIXT.

Section 4.1 of the online Robustness Appendix also compares FVIXT with its full-sample version, FVIX, which was used in earlier papers (Barinov, 2012, 2013, 2018). FVIXT and FVIX have correlation of 0.991 and very similar alphas; consistent with that, the alphas of various versions of the HMD strategy do not change much if I replace FVIXT with FVIX.

Similar evidence emerges when I try to remove factor structure from FVIX in a different way: by dropping distressed (and then also volatile) firms from the base assets. This exercise assures than FVIX does not explain the distress risk puzzle due to a strong tilt away from distressed stocks within FVIX.[37] 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.

My conclusion is that distressed firms are spread out across VIX sensitivity quintiles: it is not like all distressed firms are concentrated in one particular VIX sensitivity quintile and all FVIX has to do is load up on this quintile to mechanically explain the distress risk puzzle.

7.3 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 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 quickly) and long-run, LR, component (that mean-reverts extremely slowly). They find that both components are priced.

In Section 9.1 of the online Robustness Appendix, I look at the HMD strategy for the full sample and for subsamples in which its alpha is the largest (volatile firms, growth firms, etc.). ICAPM with the market factor and FVIX generates (absolute) average alpha

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

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 per month – some improvement over CAPM with its average alpha of 63 bp per month, but far from the two-factor ICAPM with the market and FVIX. The SR beta is negative and mostly significant, while the LR beta is positive and significant, indicating that the positive-alpha HMD 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), and the larger alpgas of various HMD portfolios when I use SR instead of FVIX suggest that VIX is a cleaner proxy for expected short-run volatility than the C-GARCH forecast.

In Section 9.4 of the online Robustness Appendix, I also look at the role of volatility shocks from long-run VaR estimated in Campbell et al. (2018), who find that exposure to these shocks can explain the value effect and several other anomalies. I find that those volatility shocks are weakly related to FVIXT, but closely related to FIVol, the factor that mimics shocks to average IVol and in part explains the value effect in Barinov and Chabakauri (2023). Since distressed firms (with negative alphas) tend to be value firms, both FIVol and volatility shocks from Campbell et al. (2018) contribute little to explaining the distress risk puzzle.

7.4 Distress Risk Puzzle and Sentiment

In Section 11 of the online Robustness Appendix, I look at potential overlap between FVIX and two new mispricing factors, MGMT and PERF, introduced by Stambaugh and Yuan (2017). I find that both factors load negatively on FVIX, and FVIX loads negatively on MGMT and PERF, but FVIX is unable to explain the alphas of MGMT and PERF, nor can MGMT and PERF materially explain the alpha of FVIX. Consistent with that, in the regressions of various versions of the HMD strategy on FVIX, MGMT, and PERF, all factors remain significant in the presence of the others. While this evidence suggests that mispricing factors play a role in explaining the distress risk puzzle, in the context of this paper a significant point 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 the online Robustness Appendix, I find that various versions of the HMD 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 at odds with the 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.

7.5 Distress Risk Puzzle and Additional Risk Factors

Herskovic et al. (2016) find that a common factor in firm-level IVol is priced in the cross-section and earns a negative risk premium. Barinov and Chabakauri (2023) find that a similar factor tracking news about average IVol in the market (FIVol) contributes to explaining the value effect. Theoretically, the volatility risk explanation of the distress risk puzzle can be easily extended to predict that FIVol will also contribute to explaining the distress risk puzzle (distressed firms will do well when all firms, on average, become more volatile).

Distressed firms tend to be value firms, but in contrast to value firms, distressed firms have negative, not positive alphas. In Barinov and Chabakauri (2023), positive alphas of value firms are explained by their negative loadings on FIVol. Thus, empirically, distressed firms are likely to load negatively on FIVol (because they tend to be value firms), and this loading will make their negative alphas more puzzling. This is observed in empirical tests in Section 9.4 of the online Robustness Appendix: FIVol is not helpful in explaining the distress risk puzzle, because FIVol picks up the value effect, and controlling for the value effect is long known to make the distress risk puzzle stronger.

Chang et al. (2013) show that innovations to market skewness are positively priced in the cross-section. I download option-implied S&P 500 skewness data from CBOE, calculate daily innovations to market skewness as residuals from the ARMA(1,1) model, and form a factor-mimicking portfolio for the innovations to market skewness (FSkew) the same way I form FVIX. When I run a spanning test in the spirit of Barillas and Shanken (2017), I find that FVIX can explain the alpha of FSkew, but not the other way around, which makes FSkew a redundant factor once FVIX is present.

Focusing on the distress risk puzzle, I replace FVIX with FSkew in the two-factor ICAPM and find that alphas of different variants of the HMD strategy become roughly 1.5 times greater, indicating lower ability of FSkew to explain the distress risk puzzle. More importantly, when I use FVIX and FSkew together to explain the distress risk puzzle, the alphas of the HMD strategy remain the same as when only FVIX is used. I conclude that the market skewness factor does not contribute any additional information about the distress risk puzzle compared to FVIX.

7.6 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, 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 the 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.

8 Conclusion

This paper predicts that distressed firms tend to perform relatively well when aggregate volatility unexpectedly increases. Since distressed firms have high market betas, they should lose more than an average firm during high volatility periods, which are also periods of declining market, but distressed firms should 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 models) during volatile periods can be a potential explanation of 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) is reduced by 80-95% in portfolio sorts and by 45-95% in cross-sectional regressions and becomes statistically insignificant. 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 a 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 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. This provides an additional reason why option-like equity of distressed firms does relatively well when aggregate volatility increases.

I also test the prediction of the paper that distressed firms do well in "bad times" using small subsamples (20-50 months) with extremely positive VIX changes, or extremely negative returns, or NBER recessions. In these subsamples, the point estimates of distressed firms' CAPM alphas are uniformly positive and economically large (1-2% per month), but usually lack statistical significance.

Consistent with my explanation of the distress risk puzzle, I also find that, first, the distress risk puzzle in the CAPM alphas 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. Second, controlling for aggregate volatility risk reduces the distress risk puzzle for volatile firms by at least 50%, and the difference in the distress risk puzzle between high- and low-volatility firms sees a similar reduction.

Also consistent with my explanation of the distress risk puzzle is the fact that aggregate volatility risk can contribute to explaining 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) creates a wider spread in option-likeness.

I also find, consistent with my explanation of the distress risk puzzle and the Johnson (2004) model, that sorting zero-leverage firms on distress probability (i.e., O-score) creates no spread in either CAPM alphas or FVIXT betas.

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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 – IVol (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 1991 to December 2016. 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

	Best	**Cred2**	**Cred3**	**Cred4**	**Worst**	**W-B**
AveCred	*A+*	*BBB+*	*BBB-*	*BB*	*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. FVIX Factor and Its Base Assets

Panel A presents average firm characteristics across base assets of FVIX, quintile portfolios sorted on historical sensitivity to VIX changes. VIX sensitivity is defined as γ from

$$Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \gamma_{\Delta VIX} \cdot \Delta VIX_t \tag{5}$$

estimated separately for each firm-month using daily returns and daily VIX changes (at least 15 valid observations are required). Panel B presents, in the first row, the average slopes on the VIX sensitivity quintiles from the factor-mimicking regression

$$\begin{aligned} \Delta VIX_t &= \gamma_0 + \gamma_1 \cdot (VIX1_t - RF_t) + \gamma_2 \cdot (VIX2_t - RF_t) + \gamma_3 \cdot (VIX3_t - RF_t) \\ &\quad + \gamma_4 \cdot (VIX4_t - RF_t) + \gamma_5 \cdot (VIX5_t - RF_t) \end{aligned} \tag{6}$$

The second and fourth row of Panel B present average returns and CAPM alphas of the VIX sensitivity quintile portfolios, and the third row presents average products of the slopes in the first row and the returns in the second row. Panel C presents alphas and factor betas of FVIX using the CAPM, the three-factor and five-factor Fama-French models, the Carhart model and the five-factor model augmented with the momentum factor. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1991 to December 2016. The sample excludes stocks priced below $5 on the portfolio formation date.

Panel A. Average Firm Characteristics across VIX Sensitivity Quintiles

	Neg	**Quint2**	**Quint3**	**Quint4**	**Pos**	**P-N**	**t(P-N)**
Size	1.600	3.841	3.883	2.989	1.150	-0.450	-4.33
Lev	0.214	0.202	0.204	0.202	0.212	-0.002	-1.23
O-score	-4.679	-6.125	-6.153	-6.042	-4.730	-0.051	-0.59
Z-score	4.769	5.249	5.130	5.072	4.821	0.052	0.30
Cred	11.43	9.454	9.212	9.741	11.79	0.362	4.16
	BB+	*BBB*	*BBB*	*BBB-*	*BB*		
MB	4.789	4.747	4.139	4.300	4.469	-0.319	-1.16
Mom	0.095	0.149	0.148	0.149	0.100	0.005	0.50
Inv	0.034	0.037	0.035	0.038	0.034	0.001	1.73
GProf	1.526	1.143	1.093	1.195	1.619	0.094	0.51
IVol	0.041	0.020	0.016	0.021	0.042	0.001	3.34
Disp	0.277	0.180	0.165	0.183	0.286	0.009	1.21
Error	0.794	0.591	0.542	0.585	0.840	0.047	1.42

Panel B. Factor-Mimicking Regressions

	Neg	Quint2	Quint3	Quint4	Pos	P-N
$\overline{\gamma_i}$	-0.129	-0.461	-0.423	-0.192	0.015	0.144
t-stat	*-22.2*	*-68.8*	*-54.9*	*-40.5*	*5.07*	*27.2*
$\overline{\boldsymbol{VIX_i - RF}}$	1.091	0.816	0.770	0.802	0.541	-0.550
t-stat	*3.66*	*3.78*	*3.43*	*3.11*	*1.49*	*-2.89*
$\overline{\boldsymbol{\gamma_i \cdot (VIX_i - RF)}}$	-0.134	-0.383	-0.335	-0.172	-0.001	0.133
t-stat	*-2.92*	*-3.87*	*-3.48*	*-3.46*	*-0.09*	*2.63*
$\boldsymbol{\alpha_{CAPM}}$	0.052	-0.023	-0.095	-0.150	-0.666	-0.717
t-stat	*0.40*	*-0.32*	*-1.57*	*-2.63*	*-4.58*	*-3.66*

Panel C. FVIXT Alphas and Factor Betas

	Raw	CAPM	FF	Carhart	FF5	FF6
$\boldsymbol{\alpha}$	-1.143	-0.381	-0.381	-0.404	-0.295	-0.317
t-stat	*-4.71*	*-4.66*	*-4.29*	*-4.34*	*-3.97*	*-4.16*
$\boldsymbol{\beta}_{MKT}$		-1.059	-1.073	-1.063	-1.114	-1.105
t-stat		*-34.8*	*-33.9*	*-31.7*	*-43.0*	*-41.1*
$\boldsymbol{\beta}_{SMB}$			0.077	0.074	0.036	0.031
t-stat			*3.12*	*3.40*	*1.90*	*1.68*
$\boldsymbol{\beta}_{HML}$			-0.028	-0.017	0.043	0.067
t-stat			*-0.79*	*-0.51*	*1.08*	*1.62*
$\boldsymbol{\beta}_{MOM}$				0.029		0.038
t-stat				*1.80*		*2.23*
$\boldsymbol{\beta}_{CMA}$					-0.082	-0.098
t-stat					-1.660	*-2.18*
$\boldsymbol{\beta}_{RMW}$					-0.138	-0.147
t-stat					*-4.60*	*-5.02*

Table 3. Distress Risk Puzzle and Aggregate Volatility Risk

The table reports value-weighted (Panel A) and equal-weighted (Panel B) percentage monthly alphas from the CAPM, the Carhart model, as well as alphas and FVIXT betas from the two-factor ICAPM with the market factor and FVIXT, and the Carhart model augmented with FVIXT, "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:

$$\begin{aligned} Ret_t - RF_t \quad = \quad & \alpha + \gamma_0 \cdot (MKT_t - RF_t) + \gamma_1 \cdot DEF_{t-1} \cdot (MKT_t - RF_t) + \gamma_2 \cdot DIV_{t-1} \cdot (MKT_t - RF_t) \\ & + \gamma_3 \cdot TB_{t-1} \cdot (MKT_t - RF_t) + \gamma_4 \cdot TERM_{t-1} \cdot (MKT_t - RF_t) \end{aligned} \tag{7}$$

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 out-of sample forecast from

$$MKT_t - RF_t = c_0 + c_1 \cdot DEF_{t-1} + c_1 \cdot DIV_{t-1} + c_3 \cdot TB_{t-1} + c_4 \cdot TERM_{t-1} \tag{8}$$

exceeds in-sample average of market risk premium. Both the Conditional CAPM (equation 3) and the predictive regression (equation 4) are estimated using expanding window and use 1986-1992 (1983-1992) as the learning sample.

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. FVIXT 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 1991 to December 2016 in Panels A1, A2, B1, and B2 and January 1993 to December 2016 in Panels A3 and B3. 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+*	
$\boldsymbol{\alpha}_{CAPM}$	0.128	-0.195	-0.068	-0.453	-0.864	0.992
t-stat	*1.92*	*-1.78*	*-0.44*	*-2.48*	*-2.69*	*2.75*
$\boldsymbol{\alpha}_{ICAPM}$	-0.045	-0.113	0.039	-0.260	-0.273	0.228
t-stat	*-0.45*	*-1.03*	*0.24*	*-1.45*	*-0.84*	*0.59*
$\boldsymbol{\beta}_{FVIXT}$	-0.451	0.216	0.280	0.505	1.549	-2.000
t-stat	*-2.73*	*2.05*	*1.14*	*1.66*	*4.44*	*-4.25*

Panel B. Equal-Weighted Returns

B1. CAPM as Benchmark Model

	Best	**Cred2**	**Cred3**	**Cred4**	**Worst**	**B-W**
AveCred	*A+*	*BBB+*	*BBB-*	*BB*	*B+*	
$\boldsymbol{\alpha}_{CAPM}$	0.269	0.205	0.160	-0.038	-0.448	0.717
t-stat	*2.36*	*1.34*	*0.77*	*-0.15*	*-2.03*	*3.26*
$\boldsymbol{\alpha}_{ICAPM}$	0.059	0.095	0.132	0.019	-0.093	0.152
t-stat	*0.46*	*0.64*	*0.67*	*0.08*	*-0.43*	*0.69*
$\boldsymbol{\beta}_{FVIXT}$	-0.549	-0.289	-0.073	0.148	0.929	-1.478
t-stat	*-1.87*	*-1.03*	*-0.20*	*0.41*	*4.42*	*-4.31*

A2. Carhart Model as Benchmark Model

AveCred	**Best** *A+*	**Cred2** *BBB+*	**Cred3** *BBB-*	**Cred4** *BB*	**Worst** *B+*	**B-W**
$\boldsymbol{\alpha}_{Carhart}$	0.175	-0.093	-0.045	-0.265	-0.461	0.635
t-stat	*3.51*	*-0.96*	*-0.33*	*-1.70*	*-1.43*	*1.90*
$\boldsymbol{\alpha}_{Carhart+V}$	0.061	-0.008	0.023	-0.130	0.022	0.039
t-stat	*1.03*	*-0.09*	*0.17*	*-0.85*	*0.08*	*0.14*
$\boldsymbol{\beta}_{FVIXT}$	-0.217	0.161	0.130	0.256	0.918	-1.136
t-stat	*-3.83*	*2.40*	*1.17*	*1.97*	*4.47*	*-5.05*

B2. Carhart Model as Benchmark Model

AveCred	**Best** *A+*	**Cred2** *BBB+*	**Cred3** *BBB-*	**Cred4** *BB*	**Worst** *B+*	**B-W**
$\boldsymbol{\alpha}_{Carhart}$	0.246	0.148	0.078	-0.140	-0.395	0.641
t-stat	*3.37*	*1.58*	*0.58*	*-0.91*	*-2.94*	*4.19*
$\boldsymbol{\alpha}_{Carhart+V}$	0.086	0.057	-0.001	-0.052	0.031	0.055
t-stat	*1.38*	*0.61*	*-0.01*	*-0.38*	*0.15*	*0.25*
$\boldsymbol{\beta}_{FVIXT}$	-0.309	-0.228	-0.174	0.044	0.478	-0.787
t-stat	*-3.37*	*-2.66*	*-1.35*	*0.32*	*3.39*	*-3.99*

A3. Conditional CAPM

AveCred	**Best** *A+*	**Cred2** *BBB+*	**Cred3** *BBB-*	**Cred4** *BB*	**Worst** *B+*	**B-W**
$\boldsymbol{\alpha}_{CAPM}$	0.179	-0.228	-0.034	-0.619	-0.806	0.985
t-stat	*2.47*	*-1.92*	*-0.21*	*-3.12*	*-2.78*	*2.94*
$\boldsymbol{\alpha}_{CCAPM}$	0.108	-0.074	-0.073	-0.394	-0.474	0.582
t-stat	*20.6*	*-7.97*	*-8.39*	*-26.3*	*-29.8*	*29.0*
$\boldsymbol{\beta_{Rec}}$	0.890	1.041	1.273	1.346	1.472	-0.581
t-stat	*130.8*	*78.4*	*45.6*	*53.4*	*39.3*	*-14.5*
$\boldsymbol{\beta_{Exp}}$	0.827	1.058	1.246	1.488	1.838	-1.011
t-stat	*49.3*	*28.4*	*23.9*	*32.1*	*34.9*	*-16.7*
$\boldsymbol{\beta_R - \beta_E}$	0.063	-0.017	0.027	-0.142	-0.366	0.429
t-stat	*3.23*	*-0.40*	*0.41*	*-2.47*	*-5.68*	*5.92*

B3. Conditional CAPM

AveCred	**Best** *A+*	**Cred2** *BBB+*	**Cred3** *BBB-*	**Cred4** *BB*	**Worst** *B+*	**B-W**
$\boldsymbol{\alpha}_{CAPM}$	0.298	0.212	0.141	-0.059	-0.526	0.823
t-stat	*2.40*	*1.27*	*0.62*	*-0.22*	*-2.15*	*3.46*
$\boldsymbol{\alpha}_{CCAPM}$	0.152	0.058	0.055	-0.207	-0.604	0.756
t-stat	*31.3*	*5.10*	*3.79*	*-10.3*	*-26.7*	*40.9*
$\boldsymbol{\beta_{Rec}}$	0.944	1.079	1.206	1.333	1.446	-0.501
t-stat	*49.0*	*43.0*	*33.2*	*33.1*	*40.1*	*-22.0*
$\boldsymbol{\beta_{Exp}}$	0.886	0.999	1.181	1.348	1.572	-0.687
t-stat	*21.8*	*26.7*	*17.8*	*17.5*	*32.3*	*-22.5*
$\boldsymbol{\beta_R - \beta_E}$	0.059	0.080	0.025	-0.016	-0.127	0.185
t-stat	*1.17*	*1.61*	*0.30*	*-0.16*	*-1.92*	*4.74*

Table 4. 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 in percent per month ($\overline{\alpha}$) 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 1991 to December 2016. The sample excludes stocks priced below \$5 at the portfolio formation date.

	Raw	$\hat{\boldsymbol{\alpha}}_{CAPM}$	$\hat{\boldsymbol{\alpha}}_{ICAPM}$	$\hat{\boldsymbol{\alpha}}_{FF}$	$\hat{\boldsymbol{\alpha}}_{FF+V}$	$\hat{\boldsymbol{\alpha}}_{Carhart}$	$\hat{\boldsymbol{\alpha}}_{Carh+V}$	$\hat{\boldsymbol{\alpha}}_{FF5}$	$\hat{\boldsymbol{\alpha}}_{FF5+V}$
Size	-0.443	-0.298	-0.536	-0.350	-0.142	-0.210	-0.180	-0.391	-0.051
t-stat	*-0.87*	*-0.64*	*-0.95*	*-0.83*	*-0.27*	*-0.48*	*-0.33*	*-0.86*	*-0.09*
MB	-0.445	-0.311	0.136	0.108	0.013	-0.048	0.037	0.622	0.688
t-stat	*-1.92*	*-1.28*	*0.51*	*0.58*	*0.06*	*-0.23*	*0.15*	*2.60*	*2.34*
Mom	1.019	0.766	0.573	0.523	0.111	0.305	0.022	-0.078	-0.745
t-stat	*2.40*	*1.90*	*1.06*	*1.33*	*0.20*	*0.75*	*0.04*	*-0.17*	*-1.25*
Rev	-0.340	-0.318	-0.568	-0.511	-0.751	-0.629	-0.737	-0.653	-0.720
t-stat	*-1.69*	*-1.46*	*-1.46*	*-2.14*	*-1.72*	*-2.13*	*-1.72*	*-2.36*	*-1.83*
Cred	-4.072	-7.338	-0.273	-7.322	-3.611	-6.872	-3.807	-3.568	-0.368
t-stat	*-1.55*	*-3.52*	*-0.10*	*-4.55*	*-1.96*	*-4.25*	*-1.85*	*-2.05*	*-0.18*

Table 5. Distressed Firms in Bad Periods of Time

Panel A looks at CAPM alphas of credit rating quintiles (Panel A1) in subsamples with the VIX index exceeding the percentile indicated in the left-most column, and then presents (Panel A2) several characteristics of these subsamples. Panel B presents similar CAPM alphas in the subsamples with market return below numbers in the leftmost column; the rightmost column of Panel B gives the number of months in these subsamples. Panel C estimates alphas of credit rating quintiles in expansions and recessions by estimating the CAPM separately during months that NBER marks as expansions/recessions. The last line of Panel C calculates the difference between the two alphas as α_{R-E} from

$$Ret_t = \alpha_{Exp} + \beta_{Exp} \cdot (MKT_t - RF_t) + \Delta\alpha_{R-E} \cdot REC_t + \Delta\beta_{R-E} \cdot REC_t \cdot (MKT_t - RF_t)\epsilon_t \tag{9}$$

where REC_t is 1 during NBER recession months and 0 otherwise. Panel D presents slopes from regressions of daily returns to credit rating quintiles on daily market returns and daily VIX changes.

$$Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \gamma_{\Delta VIX} \cdot \Delta VIX_t \tag{10}$$

Panel A. CAPM Alphas in DVIX Percentile Subsamples

	A1. Quintile Sorts						A2. Sample Characteristics			
$\boldsymbol{VIX >}$	**Best** *A+*	**Cred2** *BBB+*	**Cred3** *BBB-*	**Cred4** *BB*	**Worst** *B+*	**B-W**	**NObs**	$\boldsymbol{VIX >}$	$\overline{\boldsymbol{MKT - RF}}$	$\boldsymbol{\%\ MKT - RF < 0}$
95th pctl	0.155	1.232	0.607	0.861	3.850	-3.695	19	35.40	-3.88	58%
t-stat	*0.28*	*2.07*	*0.52*	*0.50*	*1.61*	*-1.38*				
90th pctl	0.238	0.608	0.801	1.018	4.935	-4.697	38	29.56	-3.62	63%
t-stat	*0.77*	*1.69*	*1.19*	*1.12*	*2.20*	*-2.13*				
85th pctl	0.127	0.641	0.262	0.667	2.536	-2.409	57	26.63	-2.80	65%
t-stat	*0.43*	*1.95*	*0.44*	*0.93*	*1.47*	*-1.37*				
80th pctl	0.164	0.361	0.156	0.557	1.352	-1.189	76	25.29	-2.14	63%
t-stat	*0.77*	*1.25*	*0.33*	*0.94*	*0.96*	*-0.81*				
75th pctl	0.165	0.053	0.001	0.347	1.022	-0.858	95	23.97	-1.55	59%
t-stat	*0.96*	*0.20*	*0.00*	*0.64*	*0.89*	*-0.72*				

Panel B. CAPM Alphas in Down Markets

	Best	Cred2	Cred3	Cred4	Worst	B-W	NObs
AveCred	*A+*	*BBB+*	*BBB-*	*BB*	*B+*		
$\boldsymbol{MKT < -3\%}$	0.085	0.479	1.225	0.102	1.699	-1.614	50
t-stat	*0.22*	*0.84*	*1.05*	*0.09*	1.43	-1.20	
$\boldsymbol{MKT < -4\%}$	-0.371	0.442	1.378	-0.632	2.085	-2.456	38
t-stat	*-0.62*	*0.58*	*0.84*	*-0.35*	1.06	-1.07	
$\boldsymbol{MKT < -5\%}$	-0.427	0.411	2.174	0.174	1.139	-1.566	29
t-stat	*-0.60*	*0.36*	*1.01*	*0.10*	0.56	*-0.74*	
$\boldsymbol{MKT < -6\%}$	-0.116	1.792	2.426	-1.642	4.217	-4.334	21
t-stat	*-0.13*	*0.98*	*0.79*	*-0.73*	1.20	*-1.09*	

Panel C. Distressed Stocks Alphas in Recessions

	Best	Cred2	Cred3	Cred4	Worst	B-W
AveCred	*A+*	*BBB+*	*BBB-*	*BB*	*B+*	
$\boldsymbol{\alpha_{Rec}}$	0.109	-0.181	0.357	0.481	0.430	-0.321
t-stat	*0.66*	*-0.30*	*0.70*	*0.77*	*0.38*	*-0.28*
$\boldsymbol{\alpha_{Exp}}$	0.132	-0.188	0.022	-0.528	-0.639	0.771
t-stat	*1.64*	*-1.66*	*0.15*	*-2.72*	*-2.18*	*2.19*
$\boldsymbol{\Delta\alpha_{R-E}}$	-0.023	0.007	0.335	1.009	1.069	-1.092
t-stat	*-0.12*	*0.01*	*0.56*	*1.55*	*0.94*	*-0.95*

Panel D. Loadings on VIX Change

	Best	Cred2	Cred3	Cred4	Worst	B-W
AveCred	*A+*	*BBB+*	*BBB-*	*BB*	*B+*	
Full Sample						
$\boldsymbol{\beta_{MKT}}$	0.847	1.076	1.060	1.280	1.529	-0.682
t-stat	*70.2*	*59.5*	*77.0*	*53.9*	*41.3*	*-15.6*
$\boldsymbol{\gamma_{\Delta VIX}}$	-0.041	0.012	0.008	0.037	0.081	-0.122
t-stat	*-9.87*	*1.55*	*2.12*	*3.87*	*5.43*	*-7.66*
Recessions						
$\boldsymbol{\beta_{MKT}}$	0.776	1.132	1.123	1.503	1.773	- 0.997
t-stat	*35.0*	*23.6*	*42.8*	*25.9*	*16.7*	*-8.80*
$\boldsymbol{\gamma_{\Delta VIX}}$	-0.064	0.047	0.022	0.138	0.208	-0.272
t-stat	*-5.12*	*2.02*	*1.60*	*3.26*	*4.19*	*-5.10*
Expansions						
$\boldsymbol{\beta_{MKT}}$	0.869	1.066	1.038	1.223	1.472	-0.603
t-stat	*61.6*	*60.3*	*73.5*	*49.3*	*43.2*	*-13.5*
$\boldsymbol{\gamma_{\Delta VIX}}$	-0.037	0.008	0.005	0.022	0.065	-0.102
t-stat	*-7.80*	*1.22*	*1.25*	*3.34*	*5.46*	*-7.24*

Table 6. Distress Risk Puzzle, Idiosyncratic Volatility, and Aggregate Volatility Risk

Panel A presents percentage monthly CAPM alphas, ICAPM alphas, and FVIXT betas for the conditional double sorts first into three groups (bottom 30%, middle 40%, top 30%) on idiosyncratic volatility (IVol) and then into quintiles on credit rating. The double sorts are repeated each month and use NYSE (exchcd=1) quintiles. IVol 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 FVIXT), and FVIXT betas of the same double-sorted portfolios. FVIXT 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 1991 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	0.440	0.237	0.286	0.154
t-stat	*3.61*	*1.96*	*1.48*	*0.85*
Cred2	0.357	0.169	0.270	0.087
t-stat	*2.14*	*1.01*	*1.13*	*0.48*
Cred3	0.401	0.282	-0.172	0.582
t-stat	*2.35*	*1.24*	*-0.56*	*2.26*
Cred4	0.386	0.153	0.111	0.257
t-stat	*1.74*	*0.64*	*0.38*	*1.11*
Worst	0.323	0.227	-0.835	1.158
t-stat	*1.60*	*0.98*	*-2.72*	*3.45*
B-W	0.117	0.010	1.120	1.004
t-stat	*0.70*	*0.05*	*3.60*	*3.03*

Panel A2. ICAPM alphas

	Low	**Med**	**High**	**L-H**
Best	0.163	0.050	0.266	-0.103
t-stat	*1.14*	*0.36*	*1.59*	*-0.48*
Cred2	0.156	0.046	0.282	-0.126
t-stat	*0.90*	*0.26*	*1.21*	*-0.66*
Cred3	0.228	0.205	-0.053	0.287
t-stat	*1.11*	*0.89*	*-0.19*	*1.17*
Cred4	0.287	0.130	0.449	-0.184
t-stat	*1.32*	*0.57*	*1.55*	*-0.72*
Worst	0.296	0.422	-0.221	0.517
t-stat	*1.43*	*1.97*	*-0.68*	*1.41*
B-W	-0.133	-0.371	0.488	0.621
t-stat	*-0.71*	*-1.81*	*1.73*	*1.98*

Panel A3. FVIXT Betas

	Low	**Med**	**High**	**L-H**
Best	-0.724	-0.489	-0.051	-0.673
t-stat	*-2.27*	*-1.60*	*-0.16*	*-2.31*
Cred2	-0.524	-0.323	0.032	-0.557
t-stat	*-1.51*	*-1.00*	*0.11*	*-2.06*
Cred3	-0.450	-0.200	0.324	-0.797
t-stat	*-1.39*	*-0.44*	*0.71*	*-3.06*
Cred4	-0.259	-0.060	0.853	-1.114
t-stat	*-0.73*	*-0.14*	*3.53*	*-3.04*
Worst	-0.072	0.509	1.602	-1.674
t-stat	*-0.28*	*1.62*	*4.90*	*-3.74*
B-W	-0.652	-0.998	-1.653	-1.000
t-stat	*-3.53*	*-4.64*	*-3.96*	*-2.43*

Panel B1. Carhart alphas

	Low	Med	High	L-H
Best	0.403	0.220	0.349	0.054
t-stat	*4.90*	*2.58*	*2.41*	*0.34*
Cred2	0.301	0.081	0.269	0.032
t-stat	*2.38*	*0.74*	*1.51*	*0.19*
Cred3	0.334	0.183	-0.199	0.561
t-stat	*2.44*	*1.23*	*-0.92*	*2.45*
Cred4	0.229	0.027	0.111	0.105
t-stat	*1.28*	*0.16*	*0.54*	*0.53*
Worst	0.157	0.072	-0.650	0.806
t-stat	*1.07*	*0.44*	*-2.61*	*2.57*
B-W	0.246	0.147	0.998	0.752
t-stat	*1.77*	*0.88*	*3.63*	*2.33*

Panel B2. Carhart+V alphas

	Low	Med	High	L-H
Best	0.201	0.097	0.350	-0.148
t-stat	*2.39*	*1.09*	*2.36*	*-0.84*
Cred2	0.142	-0.029	0.249	-0.107
t-stat	*1.12*	*-0.28*	*1.48*	*-0.63*
Cred3	0.181	0.122	-0.171	0.374
t-stat	*1.26*	*0.80*	*-0.78*	*1.68*
Cred4	0.115	-0.036	0.307	-0.210
t-stat	*0.69*	*-0.20*	*1.38*	*-1.10*
Worst	0.065	0.133	-0.147	0.212
t-stat	*0.40*	*0.78*	*-0.61*	*0.66*
B-W	0.136	-0.036	0.497	0.361
t-stat	*0.82*	*-0.22*	*2.10*	*1.11*

Panel B3. FVIXT Betas

	Low	Med	High	L-H
Best	-0.174	-0.025	0.291	-0.465
t-stat	*-3.69*	*-0.60*	*4.62*	*-7.28*
Cred2	0.070	0.213	0.583	-0.512
t-stat	*1.03*	*2.43*	*6.35*	*-8.31*
Cred3	0.111	0.318	0.827	-0.709
t-stat	*1.13*	*2.81*	*6.51*	*-7.12*
Cred4	0.247	0.473	0.968	-0.725
t-stat	*2.15*	*3.77*	*10.51*	*-9.37*
Worst	0.401	0.692	1.121	-0.720
t-stat	*5.24*	*6.24*	*11.56*	*-7.47*
B-W	-0.575	-0.717	-0.829	-0.255
t-stat	*-9.44*	*-8.80*	*-8.63*	*-2.44*

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

Panel A presents percentage monthly CAPM alphas, ICAPM alphas, and FVIXT 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 FVIXT), and FVIXT betas of the same double-sorted portfolios. FVIXT 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 1991 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	0.381	0.388	0.359	0.022
t-stat	*1.80*	*2.29*	*3.40*	*0.11*
Cred2	0.368	0.346	0.190	0.178
t-stat	*1.28*	*1.90*	*1.65*	*0.76*
Cred3	0.213	0.216	0.335	-0.122
t-stat	*0.69*	*0.92*	*2.69*	*-0.43*
Cred4	-0.117	0.139	0.044	-0.132
t-stat	*-0.43*	*0.59*	*0.23*	*-0.59*
Worst	0.147	-0.111	-0.511	0.658
t-stat	*0.41*	*-0.44*	*-2.36*	*1.92*
B-W	0.235	0.499	0.870	0.636
t-stat	*0.90*	*2.02*	*3.21*	*2.24*

Panel A2. ICAPM alphas

	Value	Neut	Growth	G-V
Best	0.226	0.160	0.130	0.096
t-stat	*1.04*	*0.82*	*1.07*	*0.49*
Cred2	0.403	0.112	0.054	0.349
t-stat	*1.58*	*0.59*	*0.45*	*1.62*
Cred3	0.198	0.015	0.317	-0.119
t-stat	*0.77*	*0.06*	*2.79*	*-0.48*
Cred4	0.066	0.148	0.089	-0.001
t-stat	*0.23*	*0.63*	*0.45*	*-0.01*
Worst	0.275	0.281	-0.057	0.332
t-stat	*0.85*	*1.13*	*-0.26*	*1.06*
B-W	-0.049	-0.121	0.187	0.236
t-stat	*-0.19*	*-0.45*	*0.64*	*0.84*

Panel A3. FVIXT Betas

	Value	Neut	Growth	G-V
Best	-0.408	-0.597	-0.601	0.193
t-stat	*-1.04*	*-1.78*	*-1.95*	*0.97*
Cred2	0.091	-0.611	-0.357	0.448
t-stat	*0.19*	*-2.04*	*-1.36*	*1.80*
Cred3	-0.041	-0.527	-0.047	0.007
t-stat	*-0.09*	*-1.38*	*-0.26*	*0.02*
Cred4	0.486	0.025	0.118	0.345
t-stat	*1.23*	*0.07*	*0.68*	*1.06*
Worst	0.336	1.027	1.189	-0.853
t-stat	*1.00*	*3.04*	*5.92*	*-2.45*
B-W	-0.744	-1.625	-1.790	-1.046
t-stat	*-1.91*	*-6.04*	*-3.93*	*-3.77*

Panel B1. Carhart alphas

	Value	Neut	Growth	G-V
Best	0.321	0.331	0.388	-0.067
t-stat	*2.48*	*3.22*	*4.40*	*-0.47*
Cred2	0.285	0.259	0.189	0.096
t-stat	*1.35*	*2.03*	*1.75*	*0.52*
Cred3	0.102	0.093	0.352	-0.250
t-stat	*0.54*	*0.61*	*2.96*	*-1.23*
Cred4	-0.272	0.010	0.034	-0.259
t-stat	*-1.38*	*0.05*	*0.21*	*-1.12*
Worst	0.212	-0.144	-0.404	0.616
t-stat	*0.94*	*-0.76*	*-2.15*	*2.13*
B-W	0.109	0.475	0.792	0.683
t-stat	*0.51*	*2.15*	*3.67*	*2.33*

Panel B2. Carhart+V alphas

	Value	Neut	Growth	G-V
Best	0.163	0.069	0.220	-0.056
t-stat	*1.48*	*0.89*	*2.15*	*-0.37*
Cred2	0.107	0.062	0.236	-0.129
t-stat	*0.82*	*0.49*	*2.14*	*-0.87*
Cred3	0.431	-0.068	-0.030	0.461
t-stat	*2.24*	*-0.42*	*-0.20*	*2.49*
Cred4	0.023	-0.046	-0.079	0.102
t-stat	*0.14*	*-0.29*	*-0.36*	*0.46*
Worst	0.288	0.126	-0.069	0.357
t-stat	*1.00*	*0.70*	*-0.35*	*1.00*
B-W	-0.124	-0.057	0.289	0.414
t-stat	*-0.42*	*-0.30*	*1.27*	*1.00*

Panel B3. FVIXT Betas

	Value	Neut	Growth	G-V
Best	-0.239	-0.381	-0.374	0.134
t-stat	*-1.71*	*-2.86*	*-1.65*	*0.69*
Cred2	0.170	-0.526	-0.272	0.442
t-stat	*0.80*	*-3.70*	*-1.45*	*2.66*
Cred3	-0.120	-0.553	-0.131	0.010
t-stat	*-0.51*	*-2.55*	*-0.78*	*0.05*
Cred4	0.543	-0.114	-0.051	0.569
t-stat	*1.80*	*-0.45*	*-0.28*	*1.99*
Worst	0.166	0.693	0.731	-0.566
t-stat	*0.56*	*2.44*	*3.46*	*-1.80*
B-W	-0.405	-1.075	-1.105	-0.700
t-stat	*-1.22*	*-4.11*	*-3.89*	*-2.66*

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 8. O-Score, Leverage, and Aggregate Volatility Risk

The table presents percentage monthly Carhart alphas and Carhart+V alphas (from the Carhart model augmented with FVIXT), and FVIXT 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. FVIXT 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 1991 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	0.216	0.275	0.157	0.148	0.069
t-stat	*1.30*	*2.46*	*1.47*	*1.05*	*0.32*
O2	0.189	0.094	0.134	0.369	-0.180
t-stat	*1.31*	*0.95*	*1.37*	*2.15*	*-0.82*
O3	0.436	0.181	0.179	0.220	0.216
t-stat	*3.14*	*1.85*	*1.61*	*1.74*	*1.08*
O4	0.413	0.068	0.161	0.109	0.304
t-stat	*2.30*	*0.62*	*1.65*	*0.63*	*1.09*
High	0.146	-0.038	0.096	0.195	-0.049
t-stat	*0.82*	*-0.27*	*0.83*	*1.07*	*-0.17*
L-H	0.070	0.313	0.061	-0.047	-0.118
t(L-H)	*0.30*	*1.84*	*0.49*	*-0.25*	*-0.39*

Panel C. FVIXT Betas

	Zero Lev	Low Lev	Medium	High Lev	Z-H
Low	0.100	0.148	-0.104	-0.281	0.382
t-stat	*0.79*	*1.18*	*-0.80*	*-2.03*	*1.93*
O2	0.159	0.160	0.121	-0.055	0.214
t-stat	*1.25*	*1.82*	*0.55*	*-0.28*	*1.07*
O3	0.171	0.174	-0.071	0.175	-0.003
t-stat	*0.93*	*1.55*	*-0.56*	*0.96*	*-0.01*
O4	0.457	0.750	0.089	0.331	0.125
t-stat	*2.91*	*5.29*	*0.69*	*1.35*	*0.36*
High	0.371	0.551	0.762	0.835	-0.464
t-stat	*1.51*	*2.51*	*4.58*	*2.81*	*-1.04*
L-H	-0.271	-0.403	-0.866	-1.117	-0.846
t(L-H)	*-1.08*	*-1.47*	*-3.88*	*-4.24*	*-2.09*