Robustness Checks for
The Bright Side of Distress Risk

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Abstract

The document collects robustness checks for the paper "The Bright Side of Distress Risk". Section 1 replaces the measure of distress used in the paper, credit rating, with O-score from Ohlson (1980) and EDF derived from the Merton (1974) model. Section 2 presents double sorts on credit rating and disagreement and double sorts on O-score and market-to-book that were omitted from the paper. Section 3 looks at the role of credit rating downgrades in creating the distress risk puzzle and the ability of aggregate volatility risk to explain the evidence in Kim (2013) that controlling for the ratio of free funds from operations to assets subsumes the distress risk puzzle. Section 4 considers alternative versions of the aggregate volatility risk factor, FVIX. Section 5 considers robustness of cross-sectional regressions results that control for several potentially related anomalies. Section 6 shows that the relation between distress and volatility survives even after controlling for leverage. Section 7 takes a look at the relation between distress, financial leverage, and operating leverage.

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1 Alternative Distress Measures

Prior research on the distress risk puzzle uses a long list of distress measures, but mostly comes to the conclusion that healthy firms have higher expected returns than distressed firms, contrary to the initial intuition. Table 1A shows that sorting firms on credit rating also produces a strong sort on several alternative distress measures, thus implying that if credit rating is related to FVIX betas, and this relation explains the negative link between credit rating and expected returns, then other distress measures will also be related to FVIX betas, and this relation will explain why sorting on these other distress measures also creates the distress risk puzzle.

Table 1A provides a direct test of this conjecture using the two most popular distress measures - O-score from Ohlson (1980) and expected default frequency (EDF) based on Merton (1974). I follow Bharath and Shumway (2008) and use the less computationally intensive "naïve" EDF, which is based on several simplifying assumptions, but is shown by Bharath and Shumway (2008) to be a better predictor of bankruptcy than other, more sophisticated versions of EDF.[1]

Similarly to Table 3 in the paper, Table 1A starts with two top panels reporting the CAPM and ICAPM alphas, as well as the FVIX betas of the quintile portfolios sorted on O-score and EDF. FVIX betas reveal that both O-score and EDF are strongly positively related to FVIX betas, as expected. In the CAPM alphas, the distress risk puzzle is relatively weak at 27 bp per month in the O-score sorts and 20 bp per month in EDF sorts (t-statistics 1.6 and 0.78). In the ICAPM alphas, the distress risk puzzle is reduced by 25-35 bp in both cases. Controlling for FVIX also expectedly explains the marginally

[1] Another advantage of considering alternative distress measures is that it extends the sample to non-rated firms that were excluded from the prior analysis that used credit rating.

significant negative alpha of high O-score firms, changing it from -24 bp to 6 bp per month.

The next two panels look at the Fama-French model, with and without FVIX. Three results stand out: first, the distress risk puzzle is now significant in both O-score and EDF sorts, second, FVIX betas are still strongly and positively related to both O-score and EDF, third, controlling for FVIX significantly reduces the distress risk puzzle in both O-score and EDF sorts and leaves it marginally significant in O-score sorts.

More careful consideration also reveals that there is significant overlap between HML and FVIX, which is expected given the evidence in Tables 4 and 6 in the paper that FVIX can explain the value effect and its relation to distress. Table 1A shows that FVIX beta differential between healthy and distressed firms is twice larger in the two-factor ICAPM with the market factor and FVIX than in the four-factor model with the market factor, SMB, HML, and FVIX. The reduction comes primarily from the FVIX beta of distressed firms, which declines by one-half, but stays significant. The overlap between FVIX and HML does not contradict my theory of the distress risk puzzle and value effect, because if the value effect is at least partly explained by volatility risk (see Barinov, 2011, for more evidence on that), then the value-minus-growth return spread (HML) is expected to pick up aggregate volatility risk.

The last two panels in Table 1A use the Carhart (1997) model as the benchmark. In the Carhart alphas, the distress risk puzzle is significant in both O-score and EDF sorts, and controlling for FVIX explains the puzzle in both sorts as well. I also observe a strong positive link between FVIX betas and both O-score and EDF, indicating the hedging ability of distressed firms against increases in aggregate volatility, as predicted by my explanation of the distress risk puzzle.

Overall, Table 1A suggests that the distress risk puzzle and its aggregate volatility risk explanation are robust to using alternative distress measures. A particularly strong robustness is exhibited by FVIX betas: no matter which distress measure and which benchmark model I use, I find that distressed firms have significantly positive FVIX betas, indicating their hedging ability against increases in aggregate volatility, and that healthy-minus-distressed differential in FVIX betas is always sizeable and statistically significant.

2 Additional Double Sorts

2.1 Distress Risk Puzzle and Analyst Disagreement

Table 2A performs double sorts, first on analyst disagreement and then on credit rating.[2] 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 of Table 2A confirm, irrespective of risk-adjustment, that the distress risk puzzle exists only in the subsample of high disagreement firms. This is consistent both with my theory of the distress risk puzzle and the empirical evidence in Avramov et al. (2009b), who perform similar double sorts and document a strong relation between the distress risk puzzle and analyst disagreement, but favor a mispricing explanation.

Compared to Table 5 in the paper that presents double sorts on credit rating and idiosyncratic volatility (instead of analyst disagreement), the distress risk puzzle in Panels A1 and B1 of Table 2A is somewhat weaker: for example, in the Carhart alphas it is significant only at 10% even for the high disagreement firms, and the negative alpha of high disagreement distressed firms is insignificant in both panels. The reason is the changed sample: Table 2A needs at least two analysts to cover the firm in order to compute the

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

disagreement measure, and severely distressed firms are often abandoned by analysts. Hence, the sample in Table 2A is smaller than in Table 5 in the paper, and some firms that are important for the distress risk puzzle are lost (for those reasons, Table 5 was chosen for the main text of the paper).

Panels A2 and B2 of Table 2A look at the alphas of the double-sorted portfolios after FVIX is added to the CAPM and Carhart model, respectively, and report two novel results. First, aggregate volatility risk is able to explain the distress risk puzzle in all analyst disagreement groups, as well as why the distress risk puzzle is stronger for high disagreement firms. Second, FVIX explains related evidence that the analyst disagreement effect of Diether et al. (2002) is stronger for distressed firms (which is again consistent with my theory).

Compared to Table 5 in the paper, Panels A2 and B2 of Table 2A are very similar in terms of FVIX ability to explain the distress risk puzzle, while FVIX is somewhat better at explaining the difference in the distress risk puzzle between high and low disagreement firms (though this difference in Table 2A is marginally significant to insignificant to start with, see Panels A1 and B1).

Panels A3 and B3 of Table 2A look at FVIX betas in the double sorts and corroborate the evidence in Panels A2 and B2. Indeed, the FVIX beta of distressed firms is significantly more positive if these firms also have high analyst disagreement. The large and positive FVIX beta of firms with bad credit rating and high analyst disagreement is also responsible for significantly more negative FVIX betas of the healthy-minus-distressed strategy in the high disagreement subsample and significantly more negative FVIX betas of the low-minus-high disagreement strategy in the distressed firms subsample (both of these strategies short bad credit rating, high analyst disagreement firms with their large and positive FVIX betas). Hence, FVIX betas in Panels A3 and B3 confirm that FVIX exposures explain why the distress risk puzzle is stronger for high disagreement firms, just as my theory of the distress risk puzzle would predict, and also why the analyst disagreement effect is stronger for distressed firms, as follows from the same theory.

Compared to Table 5 in the paper, FVIX betas in Panels A3 and B3 of Table 2A look very similar, with the weakly significant FVIX beta in the bottom right corner (the difference in the distress risk puzzle between high and low disagreement firms) being the exception, but this exception is consistent with the lack of significance in the same corner of Panels A1 and B1.

Panel C of Table 2A presents average credit rating in the double-sorted portfolios, and finds that the spread in credit rating between best and worst credit rating quintiles is somewhat wider for low disagreement firms, which works against the hypothesis that the positive relation between the distress risk puzzle and disagreement is mechanical.

In Panel C of Table 5 in the paper, where the double sorts were on credit rating and idiosyncratic volatility, the similar spread in credit rating was flat across idiosyncratic volatility groups. However, both Panel C of Table 5 in the paper and Panel C of Table 2A agree that the best-minus-worst spread in the low disagreement/volatility group resembles the one-minus-four quintile spread from single sorts on credit rating (reported in the rightmost column of Panel C), while best-minus-worst spread in the high disagreement/volatility group resembles the two-minus-five quintile spread from the single sorts.

Panel D of Table 2A presents the average number of firms in the double sorts on credit rating and idiosyncratic volatility and finds that portfolios are rather balanced, probably even more balanced than in Panel D of Table 5 in the paper, which reveals some expected concentration of firms in the best credit rating, lowest volatility portfolio and in the worst credit rating, highest volatility portfolio.

2.2 Double Sorts on O-Score and Market-to-Book

Table 3A repeats the analysis in Table 6 in the paper replacing credit rating with O-score, which makes the sample larger (O-score is available for many non-rated firms) and makes the results easier to compare with Griffin and Lemmon (2002), who also perform double sorts on O-score and market-to-book. The results in Table 3A are similar to Table 6 in the paper, indicating that the relation between the distress risk puzzle and market-to-book, as well as the aggregate volatility risk explanation of this relation, do not depend on which measure of distress one uses.

In particular, Table 3A shows that the distress risk puzzle comes almost exclusively from growth firms, for which it is significantly (by 44-55 bp per month) stronger than for value firms, and that distressed growth firms have by far the most negative CAPM/Carhart alpha in the double sorts on O-score and market-to-book. All these regularities are explained by controlling for FVIX: the negative alpha of distressed growth firms is reduced to being within 13 bp of zero after FVIX is added to the CAPM or Carhart model, the healthy-minus-distressed alpha differential disappears or becomes visibly smaller, and FVIX betas reveal a strong hedging power of distressed growth firms and an increase in aggregate volatility risk exposure of the healthy-minus-distressed strategy as one moves from the value subsample to the growth subsample.

Panels A1 and B1 of Table 3A also show, consistent with both the evidence in Griffin and Lemmon (2002) and my explanation of the distress risk puzzle and value effect, that the value effect is coming primarily from distressed firms (this is particularly visible in the Carhart alphas). Further analysis reveals, consistent with my view of the distress risk puzzle and value effect, but inconsistent with the mispricing view in Griffin and Lemmon (2002), that controlling for FVIX largely explains the stronger value effect for distressed firms, and why it is larger than the value effect for healthy firms. In particular, Panels A3 and B3 record that the value-minus-growth strategy has a significantly negative FVIX beta only if performed in the distressed subsample.

Panel C of Table 3A reveals a problem with the double sorts on O-score and market-to-book: as Panel C shows, sorting growth firms on O-score produces almost twice larger spread in O-score than sorting value firms on O-score, which suggests that the link between the distress risk puzzle and market-to-book in Table 3A may at least partly be mechanical.

This problem can be potentially fixed by making the double sorts unconditional, but in this case, first, the spread in market-to-book between healthy and distressed firms will be similarly different in different market-to-book groups, thus changing the degree to which the value effect works against the distress risk puzzle different market-to-book groups, and second, most firms will fall on the antidiagonal joining distressed value firms and healthy growth firms.

As Panel C of Table 6 in the paper shows, credit rating is not as strongly related to market-to-book, and conditional sorts work better in the double sorts on credit rating and market-to-book, which was the reason to report those in the main text and defer the original Griffin and Lemmon (2002) sorts to this appendix.

3 Alternative Explanations

3.1 Distress Risk Puzzle around Downgrades

Avramov et al. (2009a, 2013) show that the effect of credit rating on future returns 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 the firms. Avramov et al. then suggest an alternative explanation of the distress risk puzzle based on the inability of some investors to foresee how devastating a potential downgrade will be for distressed firms and the inability of other, rational investors to short overpriced distressed firms due to short-sale constraints.

My explanation of the distress risk puzzle and the one suggested by Avramov et al. are not mutually exclusive. In particular, Avramov et al. find that the frequency of downgrades is only weakly related to the business cycle. Therefore, the evidence in Avramov et al. that distressed firms react to downgrades much more negatively than healthy firms does not contradict the evidence I find in this paper that distressed firms tend to perform unexpectedly well when aggregate volatility unexpectedly increases. However, it is interesting to evaluate the relative importance of the two explanations of the distress risk puzzle.

Panel A of Table 4A repeats the analysis of Avramov et al. (2009a) and looks, in the first row, at Carhart alphas of credit rating quintiles with the six months prior and after downgrades omitted. Similar to Avramov et al. (2009a), the first row of Panel A finds that the distress risk puzzle is reduced to only 16 bp per month (from 44 bp per month in Table 3 in the paper) if the period just around the downgrade is omitted.

The FVIX betas in Panel A show, however, that removing downgrades does not eliminate the relation between credit rating and aggregate volatility risk. Why then this risk differential is not reflected in the Carhart alphas? The reason is the look-ahead bias brought about by eliminating months after portfolio formation when downgrades occur. As Avramov et al. (2013) show, firms with bad credit rating witness more frequent and more severe downgrades and subsequent delistings for performance reasons. Hence, returns to distressed firms will exhibit a higher upward bias than returns to healthy firms if future downgrades are removed from the sample.

In Panel B, I eliminate the look-ahead bias by removing from the sample only the firms that experienced a downgrade in the portfolio formation month or in the six months prior. I observe that the distress risk puzzle is back at 50 bp per month, t-statistic 3.53, and it is largely explained by the FVIX factor. I conclude that the disappearance of the distress risk puzzle when the time around downgrade is removed is largely look-ahead bias.

Avramov et al. (2009a) show that, for distressed firms only, stock prices are slow to incorporate the effect of the downgrade. Not only the month of the downgrade for distressed firms is very bad, but they also continue to post losses for a few months after. Panel C tests the hypothesis of Avramov et al. that the distress risk puzzle arises because of the slow reaction of investors to downgrades. I do find, looking only at the firms that had a downgrade in the month of sorting on credit rating or in the six months prior to that, that the distress risk puzzle and the negative alphas of distressed firms are numerically larger in this subsample.[3] Yet, FVIX largely explains both of them, suggesting that one cannot reject the hypothesis of no delayed reaction to downgrades on part of distressed firms once their negative exposure to aggregate volatility risk is accounted for.

The main argument in Avramov et al. is that the distress risk puzzle should not be realized around downgrades only, because if healthy firms beat distressed firms due to

[3] In Panel C, the alpha of the healthy-minus-distressed strategy is statistically insignificant, and the alpha of distressed firms is marginally significant despite their large magnitude (55 bp per month) due to the small number of firms with a recent downgrade I observe each month.

higher risk of healthy firms, this risk premium should be seen for most firms most of the time. This argument, however, implicitly assumes that no alpha differential equals no risk premium, which is only true if the model used to compute the alphas controls for risk appropriately. However, as, for example, the last row of Panel A shows, this is not true for the Carhart model (or any other model without an aggregate volatility risk factor), because in the periods without future downgrades distressed (healthy) firms have positive (negative) FVIX betas, indicating their low (high) risk. Similarly, in Panel D, which excludes only future downgrades from the sample, the aggregate volatility risk differential between healthy and distressed firms is still clearly visible.

Hence, what we observe in the credit rating sorts after excluding future downgrades is positive "abnormal returns" to distressed firms, which are, however, non-tradable, because they result from look-ahead bias. The risk differential is still there even with future downgrades omitted, as evidenced by the difference in FVIX betas, but its realization in average returns is masked by the look-ahead bias.[4]

3.2 Distress Risk Puzzle and Funds from Operations

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

Since FFO is potentially the variable behind the distress risk puzzle, Panel A of Table 5A looks at single sorts on FFO and the ability of FVIX to explain the resulting alphas.

[4] I have also experimented with dropping the recent financial crisis (2007-2009 or December 2007 - June 2009) from the sample and found that both the distress risk puzzle and its volatility risk explanation are not materially affected. This is consistent with the evidence in Avramov et al. (2013) that downgrades are primarily firm-specific shocks.

I find that sorting on FFO creates the high-minus-low alpha spread of roughly 45 bp per month both in the CAPM and Carhart model. In the CAPM, the spread is driven primarily by the negative alphas of low FFO (mainly distressed) firms, in the Carhart models, both low and high FFO quintiles contribute equally. The low-minus-high alpha spread is reduced to statistically insignificant 15-21 bp per month when I control for FVIX, and the alphas of the lowest FFO quintile are within 5 bp of zero. I also observe that the lowest FFO quintile (mainly distressed firms) loads positively on FVIX. This result underscores that my theory of distress risk puzzle is consistent with the evidence in Kim (2013): FFO does explain the relation between O-score and expected returns, but the relation between FFO and expected returns is in turn explained by the same FVIX that explains the relation between O-score and expected returns.

In Panels B and C of Table 5A, I test whether FFO is really behind the distress risk puzzle as Kim (2013) claims. Panel B reproduces in my sample period the main result in Kim (2013): making the sorts on O-score conditional on FFO kills the ability of O-score to predict future alphas. The alphas in the conditional O-score sorts are largely flat, irrespective of whether they are calculated using the CAPM, Carhart model, or the five-factor model with the three Fama-French factors, the momentum factor, and FVIX. The FVIX betas are also flat across the conditional O-score sorts.

Panel C, however, suggests that the result in Kim (2013) that FFO subsumes the distress risk puzzle is specific to O-score. When I make sorts on credit rating conditional on FFO, I observe the healthy-minus-distressed alpha spread that is very close to what it was in Table 3 in the paper (unconditional sorts). The ability of FVIX to explain the distress risk puzzle in the credit rating sorts and the relation between FVIX betas and credit rating are also unaffected by conditioning on FFO.

In untabulated tests, I make sorts on O-score and credit rating conditional on accruals rather than FFO. I still find significant distress risk puzzle in both cases after controlling for accruals this way, and the ability of FVIX to explain it is unaffected. I then look at single sorts on accruals and find that FVIX is not able to explain the accrual anomaly. The combination of these results suggests that the accrual anomaly and the distress risk puzzle are largely unrelated.

4 Alternative FVIX Versions

4.1 Different Base Assets

The first robustness check concerns the base assets for the factor-mimicking regression. The baseline FVIX used in the paper uses quintile portfolios pre-sorted on historical return sensitivity to VIX changes. In this section, I also use two-by-three sorts on size and market-to-book from Fama and French (1993) or ten Fama-French (1997) industry portfolios as alternative base assets. Returns to both sets of base assets are from Kenneth French's website.

Industry portfolios are a particularly stringent robustness check, since they are known to have little factor structure. FVIX based on industry portfolios (FVIXind) is unlikely to pick up the role of any other factor, but might also be weaker due to smaller variation in volatility risk exposure between the industry portfolios.

Panel A of Table 6A presents the correlation matrix for the alternative FVIX factors and estimates all correlations between the pairs (FVIX and FVIX6, FVIX and FVIXind, FVIX6 and FVIXind) at 0.98, suggesting that all versions of FVIX are very similar. Panel B presents descriptive statistics and finds more differences: while FVIX and FVIXind seem very similar in terms of average returns, CAPM alphas, volatility and risk-reward ratios, FVIX6 has lower factor risk premium (-34.7 bp per month vs. -46.3 bp and -44.8 for FVIX and FVIXind, respectively), which is not compensated by lowe volatility and thus results in a lower appraisal ratio (-0.207 vs. -0.337 and -0.297).

Panel C-E report alphas and betas of all FVIX versions. The alphas are negative and significant irrespective of the model I use, from the CAPM to the five-factor Fama and French (2015). All FVIX versions have very negative market beta (which is to be expected, since change in VIX, the variable FVIX mimics, and market return have correlation of -0.675), are not significantly related to HML and MOM, but are positively related to SMB (as Barinov and Chabakauri, 2019, and Barinov, 2013, find, firms with high idiosyncratic volatility/analyst disagreement load positively on FVIX, and these firms are usually small), negatively related to CMA and RMW. The latter relation is consistent with the finding of this paper that distressed firms load positively on FVIX - unprofitable firms tend to be distressed, and RMW shorts unprofitable firms.

Table 7A uses FVIX6 and FVIXind to explain the returns to the healthy-minus-distressed strategy, both for all firms and in high volatility and growth subsamples. I find that FVIX6 and FVIXind betas of the healthy-minus-distressed portfolio are always significantly negative and more negative in growth and high volatility subsample than in value and low volatility subsample.

I find that while on average FVIX betas (column three), FVIX6 betas (column five), and FVIXind betas (column seven) are close to each other, FVIXind betas are somewhat smaller than FVIX betas (-0.89 vs. -0.76 average), while FVIX6 betas are on average larger (-1.08). The factor risk premium of FVIXind is similar to that of FVIX, and both are larger than that of FVIX6, so the average betas above lead to the ICAPM with FVIXind and FVIX6 producing larger average alphas (21 bp and 18 bp per month, respectively, vs. 7

bp per month for the baseline ICAPM with FVIX). However, the differences above are small. All ICAPM alphas are insignificant, all FVIX betas (except for FVIX beta of OMB portfolio) are highly significant, irrespective of what version of FVIX I use, so the overall conclusion from Tables 6A and 7A is that the performance of FVIX does not depend on the base assets used to form FVIX.

4.2 Fully Tradable FVIX

The baseline FVIX is constructed using a single, full-sample factor-mimicking regression. While this is a standard technique of factor-mimicking since Breeden et al. (1989), potential look-ahead bias may be a concern. On the other hand, the look-ahead bias may be absent if investors are more informed than the econometrician. For example, the VIX index was launched in January 1986, but investors most probably were learning expected market volatility through other means long before that and may have figured out the way to map its innovations into return space decades before the econometrician was able to do so. That is, in January 1986 investors may have known the weights of the base assets necessary to create FVIX, which the econometrician was able to learn only in December 2017 by running the full-sample factor-mimicking regression.

In order to eliminate completely all look-ahead bias concerns, I construct a fully tradable version of FVIX, called FVIXT, using 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 keep adding new data as time goes by. That is, the return to FVIXT in January 1991 is the weights obtained using the 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 February 1988 to

January 1991 times the returns in February 1991, and so on.

The last row in Panel A of Table 6A shows correlations of FVIXT with other versions of FVIX. The correlation with FVIX is 0.99, while the correlations with FVIX6 and FVIXind are both close to 0.97. The last row in Panel B of Table 6A presents descriptive statistics for FVIXT: it has the lowest average return and one of the lowest alphas, but its Sharpe and appraisal ratios are the highest. This is largely the effect of losing the outlier of October 19, 1987: in untabulated results, I find that if I drop 1986-1990 from the sample and perform a full-sample factor-mimicking regression to form a truncated version of FVIX, the descriptive statistics will be very close to the ones of FVIX.

Panel F of Table 6A presents alphas and betas of FVIXT from several models, from the CAPM to the five-factor Fama-French model. The alphas and betas of FVIXT are very close to those of the baseline FVIX, with FVIXT having somewhat smaller SMB and RMW betas. Overall, Table 6A finds no traces of look-ahead bias in FVIX.

The third and fourth columns from the right in Table 7A use FVIXT to explain the alphas of the arbitrage portfolios capturing the distress risk puzzle and its cross-section. After controlling for FVIXT, all alphas come out insignificant, except for the alpha of CredDisp portfolio, which measures the difference in the distress risk puzzle between high and low disagreement firms, which is marginally significant at 10% level. The average alpha generated by the ICAPM with FVIXT equals 17 bp per month, as compared to 7 bp per month in the ICAPM with the baseline FVIX.

Likewise, all FVIXT betas are negative and significant, except for FVIXT beta of OMB, which had insignificant or marginally significant FVIX beta when other modifications of FVIX were used. The average FVIXT beta in Table 7A is -1.19, which is larger than the average beta with respect to other versions of FVIX, but FVIXT, as Table 6A shows, has lower factor risk premium than other FVIX versions.

The evidence in Table 7A shows that FVIXT, a fully tradable version of FVIX, has explanatory power very similar to FVIX, so the potential look-ahead bias in FVIX is unlikely to be an issue.

To sum up, my main result that distressed firms are hedges against aggregate volatility risk, and this property explains their low expected returns, is robust to a long list of modifications of the aggregate volatility risk factor, which lends further support to the results in the paper.

4.3 Purging FVIX of Distressed Firms

Similar evidence emerges when I try to remove confounding factor structure from FVIX in a different way: by dropping distressed firms from the base assets. This exercise makes sure than FVIX does not explain the distressed risk puzzle due to a strong tilt away from distressed stocks within FVIX. Still, it is also worth noting that such tilt, if it exists, would also be a strong confirmation of my main hypothesis that firm-specific distress measures are strongly correlated with aggregate volatility risk exposures.

FVIXtr factor drops from the base assets all firms with credit rating in the worst credit rating quintile (normally those are firms with S&P credit rating B+ and below). I also drop firms that do not have credit rating, since those firms more likely than average to be distressed. To the extent that some firms without credit rating are financially healthy firms with no publicly traded debt, my purging of FVIX is an overkill that tosses not only all distressed firms, but also some other firms as well.

Panel A of Table 6A shows that FVIXtr, purged of many firms in the sample, including distressed ones, still has correlations of 0.975-0.984 with other versions of FVIX. Panel B also reports that FVIXtr has average return, Sharpe ratio and the CAPM alpha very close to the ones of baseline FVIX (for example, their alphas compare as -46.7 bp vs. 46.3 bp). FVIXtr is less positively skewed than FVIX, but its volatility is marginally higher.

Panel G of Table 6A again reports that FVIXtr is close to baseline FVIX (as well as other versions of FVIX). The only visible difference is that in the Fama-French five-factor model (FF5) and FF5 augmented with momentum (which yields FF6), FVIXtr has significant HML and momentum betas, but the FF5 and FF6 of FVIX and FVIXtr are still within one basis point of each other.

Lastly, in Table 7A I find that removing distressed firms from the base assets does not materially affect the ability of FVIXtr to explain the distress risk puzzle and the cross-sectional dependence of the distress risk puzzle on market-to-book and idiosyncratic volatility. In Table 7A, the baseline ICAPM with FVIX yields the average absolute alpha of 15.4 bp per month and average FVIX beta of -0.945, while replacing FVIX with FVIXtr in the rightmost two columns yield the average absolute alpha of 17.5 bp per month and average FVIX beta of -0.970.

5 Distress Risk Puzzle and Related Anomalies

5.1 Controlling for Idiosyncratic Volatility, Analyst Disagreement, and Past Maximum Daily Return

Conrad et al. (2014) show that distressed companies also tend to have extremely positive returns and thus establish an overlap between the distress risk puzzle and Bali et al. (2011) maximum effect, as well as Ang et al. (2006) idiosyncratic volatility effect. Panels A and B of Table 8A add to the controls in Table 3 in the paper the maximum daily return in the past month and idiosyncratic volatility, respectively.

Columns two, four, and six (CAPM, Fama-French, Carhart alphas) find that the distress risk puzzle indeed overlaps with both anomalies (in Panels A and B, the slopes on the credit rating variable are smaller by roughly one-third compared to Table 3 in the paper), but the overlap is far from complete, since credit rating stays significant in the presence of either the maximum daily return or idiosyncratic volatility, just like those two variables also stay significant in the presence of credit rating.

Columns three, five, and seven of Panels A and B add FVIX to the models in columns two, four, and six and find that FVIX can largely explain both the distress risk puzzle and the two anomalies that Conrad et al. (2014) find are related to the distress risk puzzle. The relative reduction in slopes on credit rating as one goes from columns two, four, and six to columns three, five, and seven is similar in Panels A and B. I conclude that FVIX is an overarching factor that explains both the distress risk puzzle and the related anomalies, and its ability to explain the distress risk puzzle goes beyond the overlap of the distress risk puzzle with related anomalies.

Panel C of Table 8A that replaces the maximum daily return and idiosyncratic volatility with analyst disagreement as the additional control variable, reaches a similar conclusion. Avramov et al. (2009b) find, using portfolio-level regressions, that credit rating subsumes the analyst disagreement effect of Diether et al. (2002). Panel C finds that in firm-level regressions the overlap is far from complete: both credit rating and analyst disagreement stay significant when used together. The coefficient on credit rating declines by 37-45% going from Table 3 in the paper to Panel C of Table 8A, though this larger decrease than in Panels A and B is caused by restricting the sample to firms covered by at least two analysts (needed to compute the analyst disagreement measure). When the alphas on the left-hand side of the regression are computed from the model with FVIX (columns three, five, and seven of Panel C), the slope on credit rating is reduced by more than 50% and becomes insignificant.

The main conclusion from Table 8A is that while there is an overlap between the distress risk puzzle and several other anomalies, as previous studies suggest, this overlap is not strong at about one-third. It is thus possible for a risk factor to explain the common part the distress risk puzzle and, e.g., the idiosyncratic volatility effect share and leave the rest of the two anomalies significant. It is also possible for a risk factor to explain the two-thirds of, e.g., the idiosyncratic volatility effect that are unrelated to the distress risk puzzle and fail to explain any part of the distress risk puzzle. The ability of FVIX to explain both the distress risk puzzle and the related anomalies suggests that FVIX captures different economic mechanisms in this case.

5.2 Cross-Sectional Regressions with Top Quintile Dummies

Table 8A establishes that the distress risk puzzle survives when I control for several anomalies the literature suggests overlap with the distress risk puzzle: the analyst disagreement effect of Diether et al. (2002), the idiosyncratic volatility discount of Ang et al. (2006), and the maximum effect of Bali et al. (2011). The latter two anomalies are known to come exclusively from the top quintile: in the sorts on IVol/Max, returns are largely flat in the first four quintiles and then take a sharp dip. A similar picture emerges in the credit rating sorts, as Table 3 in the paper shows. Therefore, Table 9A in this document tests the robustness of results in Table 4 in the paper to replacing, in cross-sectional regressions, the variables creating the aforementioned anomalies by dummy variables for the top quintile: for example, TopIVol dummy is one if the firm falls into the top idiosyncratic volatility quintile and zero otherwise.

Panel A of Table 9A presents the Brennan et al. (1998) cross-sectional regressions with firm-level CAPM alphas on the left-hand side. The main takeaway from Table 9A is that the overlap between the distress risk puzzle and the anomalies above is at most 20%. For example, column one reports, controlling for well-known anomalies like the value effect, momentum, and short-term reversal, the slope on the TopCred dummy equal to -0.386 (which corresponds to 38.6 bp per month underperformance of firms in the worst credit rating quintile compared to firms in the other four quintile). In column three, which controls for TopIVol dummy, the slope on TopCred is -0.309, exactly 20% smaller - that is, firms in the worst credit rating quintile that are not in the top IVol quintile still underperform by -30.6 bp per month. Likewise, column two reports the slope on TopIVol (prior for controlling for TopIVol) at -0.365, while column three controls for TopCred and reports the slope on TopIVol that is 20% smaller (-0.289).

Columns four and five establish a similar amount of overlap between the distress risk puzzle and the maximum effect of Bali et al. (2011), and columns six and seven find no overlap between the distress risk puzzle and the profitability effect that is the basis of the new RMW factor in the five-factor Fama and French model.

The point estimates of slopes on TopCred and TopDisp in columns nine and ten also suggest that the overlap between the distress risk puzzle and the analyst disagreement effect of Diether et al. (2002) is about 20%. TopCred and TopDisp become marginally insignificant if used together, but this is largely an artefact of a small cross-sectional sample: more than one-half of firms that are covered by at least two analysts do not have a credit rating and vice versa. Column eight reruns the regression in column one (with TopCred only) for the subsample of firms with at least two analysts following them and shows that the main deterioration in TopCred slope and its significance come because of restricting the sample.

Lastly, column eleven performs a kitchen sink regression with all top quintile dummies except for TopDisp (in order not to restrict the sample too much). Consistent with Bali et al. (2011), TopIVol and TopMax show significant overlap and become significant only at the 10% level. TopGProf and TopCred remain significant and their slopes are little changed in the kitchen sink regression.

The overall conclusion from Panel A of Table 9A is similar to the one the paper draws from its Panels B-D of Table 4: as the previous literature suggested, there is an overlap between the distress risk puzzle and the anomalies discussed above, but both regressions with rank variables in the paper and regressions with top quintile dummies in Table 9A find that this overlap is small, around 20-35%.

Hence, if a risk factor explains the disagreement effect or the maximum effect, this risk factor is not mechanically guaranteed to explain the distress risk puzzle. With the overlap between the anomalies being that small, a risk factor can explain the 70-80% of the disagreement effect or the maximum effect that does not overlap with the distress risk puzzle and thus be a near perfect explanation of the former, but completely unrelated to the latter.

Panel B of Table 9A repeats Panel A with the left-hand side variable changed to firm-level alphas from the two-factor ICAPM with the market factor and FVIX. The main message of Panel B is that none of the top quintile dummies are significant once the left-hand side variable is adjusted for aggregate volatility risk. Thus, FVIX explains several anomalies at once, as a good risk factor should do, and its explanatory power, as Panel A suggests, does not come from the fact that the anomalies in question are so tightly related that anything that explains one of them will surely explain the other. To the contrary, Panel B presents the evidence that FVIX explains several anomalies that are distinct from each other.

6 Descriptive Statistics with Leverage Control

6.1 Unlevering Uncertainty Measures

The extension of Johnson (2004) model presented in the Theory Appendix[5] argues that equity, thought of as a call option on the assets, has hedging power against aggregate volatility risk, and this hedging power increases if there is more uncertainty about the value of the assets. Table 1 in the paper shows that uncertainty measures for distressed firms are several times greater than for healthy firms. However, those measures apply to equity and can be higher for distressed firms because they are more levered.

Since the uncertainty measures in the paper are essentially standard deviations, it is possible to unlever them and turn them into asset-level uncertainty measures the same way one unlevers beta. The textbook formula for unlevering beta is

$$\beta_{Assets} = \frac{\beta_{Equity}}{1 + (1 - T) \cdot \dfrac{D}{E}}$$

where T is the corporate tax rate and $\dfrac{D}{E}$ is debt-to-equity ratio. Debt-to-equity ratio can be derived from the leverage measure used throughout the paper as $\dfrac{D}{E} = \dfrac{Lev}{1 - Lev}$. The corporate tax rate T is set to either 35% (the top corporate tax rate for all but two years in the sample) or borrowed from the WRDS database based on calculations in Blouin et al. (2010), who estimate marginal tax rate for each Compustat firm with enough data.

In Table 10A, I plug into this formula, instead of beta, measures of firm-specific uncertainty, such as analyst disagreement (Disp), analyst forecast errors, idiosyncratic volatility

[5] Available at http://faculty.ucr.edu/∼abarinov/Theory Appendix Distress

(IVol), etc. - for example, for IVol the formula becomes

$$IVol_{Assets} = \frac{IVol_{StockReturns}}{1 + (1 - T) \cdot \dfrac{D}{E}}$$

The panels in Table 10A, named after the uncertainty measure they tabulate across credit rating quintiles, first present medians of raw, equity-level uncertainty measures (thus repeating Panel B of Table 1 in the paper), then present medians of unlevered, assets-level uncertainty measures with the formula using T=35%, and then present similar unlevered measures with the formula using Blouin et al. marginal tax rates.

Table 10A shows that the magnitude of the uncertainty differential between healthy and distressed firms indeed shrinks by a factor of two once leverage is controlled for, but stays highly significant - at the assets level, distressed firms have 50% (Panel A, idiosyncratic volatility) to several times more uncertainty (Panel D, analyst forecast errors). Panel B also tabulates market betas and shows that the difference in the uncertainty measures is truly idiosyncratic: distressed firms have higher market betas, but similar unlevered betas compared to healthy firms. That is, the systematic risk of assets is similar for distressed and healthy firms, but distressed firms still have more volatile assets that generate more volatile/uncertain earnings, cash flows, etc. This conclusion does not seem to depend on what I assume about the corporate tax rate.

6.2 Orthogonalizing Uncertainty Measures to Leverage

The unlevering formula in the previous subsection is simple and intuitive, but is based on some simplifying assumptions, e.g., it assumes that volatility of debt value is zero (or very small compared to volatility of equity). This assumption is unlikely to hold for distressed firms, so in Table 11A I try a different way of controlling for leverage when comparing firm-specific uncertainty measures. Table 11A reports, across credit rating quintiles, median residuals ϵ from cross-sectional regressions of log of (one plus) uncertainty measures on log of (one plus) leverage and its square:

$$\epsilon = \log(1 + U_t) - c_0 - c_1 \cdot \log(1 + Lev_{t-1}) - c_2 \cdot \log^2(1 + Lev_{t-1})$$

The regressions are estimated for the full cross-section of firms in each year and leverage is lagged by one year to avoid mechanical correlation between market cap and volatility. The squared term is added because residuals from linear regression tend to form a U-shape in the sorts on variables related to the variable one orthogonalizes to. Negative residuals indicate low levels of uncertainty compared to other firms with similar leverage, and vice versa.

The conclusions from Table 11A are similar to conclusions from Table 10A. The magnitude of the difference in orthogonalized uncertainty measures is, in most cases, materially smaller than the difference in raw uncertainty measures. Yet, the former difference is still large and significant, and I observe strong monotonic relation between credit rating and uncertainty measures orthogonalized to leverage, with best credit rating firms having significantly negative residuals, and worst credit rating firms having significantly positive residuals that are larger than those in any other credit rating quintile.

Hence, assets of distressed firms indeed have more uncertainty and firm-specific volatility than assets of healthy firms, and this higher uncertainty creates makes equity of distressed firms a hedge against aggregate volatility risk.

7 Distress and Operating Leverage

Operating leverage is an additional channel that can make distressed firms option-like. The extension of Johnson (2004) model in the Theory Appendix focus on financial leverage as the reason why distressed firms are hedges against aggregate volatility risk, but operating leverage can also contribute. While the financial leverage and operating leverage channels are not mutually exclusive, it is interesting to gauge their relative importance.

In the first row Panel A in Table 12A, I report, across credit rating quintiles, median financial leverage (Lev) and several measures of operating leverage. The second row of Panel A tabulates median OpLev, the ratio of the sum of costs of goods sold (COGS) and sales, general, and administrative expenses (SG&A) to book value of equity. I also take a separate look on the role of fixed costs (SG&A) and report the median ratio of SG&A to book value of equity in the next row. Another type of fixed costs that is becoming more important is R&D expense. The last two rows of Panel A report, for each credit rating quintile, the median ratios of R&D to total assets and R&D to market capitalization of the firm.

The first row reveals expectedly strong relation between credit rating and financial leverage, which more than triples as one goes from best to worst credit rating quintile. The relation between credit rating and operating leverage is significant, but more subdued: operating leverage in the worst credit rating quintile is only 30% higher than in the best credit rating quintile, and in the middle three quintiles operating leverage is largely flat.

Further analysis reveals that the relation of credit rating and operating leverage is all about COGS: SG&A-to-book-value is unrelated to credit rating, and the message about the importance of R&D and distress is mixed: R&D-to-assets ratio is lower rather than higher for distressed firms, and R&D-to-market-cap ratio is, to the contrary, higher for distressed firms.

Overall, I conclude from Panel A of Table 12A that the relation between credit rating and financial leverage is stronger than the relation between credit rating and operating leverage, and it is thus more likely that it is higher financial leverage rather than higher operating leverage that makes distressed firms hedges against aggregate volatility risk.

Panel B approaches the potential role of operating leverage in generating lower aggregate volatility risk of distressed firms from a different angle: it sorts firms on operating leverage and verifies directly whether these sorts create the spread in the CAPM alphas similar to sorts on credit rating (negative CAPM alphas for high operating leverage firms and vice versa) and whether operating leverage is related to FVIX betas.

As Panel B reveals, neither value-weighted nor equal-weighted alphas of high and low operating leverage are significantly different from each other, and in value-weighted returns, where the spread is economically meaningful (24 bp per month), it has the wrong sign. Likewise, in equal-weighted returns FVIX betas are flat across operating leverage quintiles, and in value-weighted returns the relation between operating leverage and aggregate volatility risk exposure is backwards, with higher operating leverage firms having significantly more negative FVIX betas.

The conclusion from Panel B is that operating leverage is unlikely to be related to aggregate volatility risk, and thus it is also unlikely that somewhat higher operating leverage of distressed firms (compared to healthy firms) can explain why distressed firms have positive FVIX betas and are thus hedges against aggregate volatility risk.

8 Average Idiosyncratic Volatility and Business Cycle

The main economic mechanism in the paper has it that distressed firms react to changes in aggregate volatility less negatively than firms with similar market betas, because higher aggregate volatility implies an increase in idiosyncratic volatility of an average firm, and the increase in idiosyncratic volatility benefits distressed firms, because their equity is similar to a call option on their assets,

The implicit assumption in this argument is that idiosyncratic and aggregate volatility are correlated in time-series. In Panel A of Table 13A, I test this assumption and run pairwise regressions of average IVol on the NBER recession dummy (one during recessions, zero otherwise) and three measures of market volatility. For each business cycle variable I run regressions with it lagged up to four quarters and leaded up to four quarters, and report the slopes in the respective columns of Panel A. For example, in the column labeled "-3" I report γ_2 from

$$\log(\overline{IVol_t}) = \gamma_0 + \gamma_1 \cdot t + \gamma_2 \cdot t^2 + \gamma_3 \cdot \log(X_{t-3}) \quad (1)$$

where X_{t-3} is one of the business cycle variables lagged by three months.

To account for the fact that IVol has trended up in 1986-2000 (see Campbell et al., 2001) and then trended down (with the exception of the Great Recession spike), I also add linear time trend and squared time trend into the regressions. Also, to make the slopes on the business cycle variables easier to interpret, I take the log of average IVol and the log of market volatility.

The numbers in the first row, which reports the slopes from the regression of average IVol on the NBER recession dummy, represent the percentage increase in IVol during recessions. IVol is on average by 20-30% higher in recessions than in expansions (the spread between the calmest period in the expansion and the most volatile period in the recession is likely to be much wider). The switch from expansion to recession predicts higher IVol for at least a year ahead and probably longer, while the increase in IVol can potentially forecast recessions one or two quarters ahead. Hence, the increase in average IVol during recessions is not short-lived.

The next rows of Panel A look at the slopes from the regressions of average IVol on the log of the VIX index, on the TARCH(1,1) forecast of market volatility, and on the log of realized market volatility (see online Data Appendix for detailed variable definitions). An increase in market volatility (expected or realized) by 1% triggers the increase in average IVol by 0.121% to 0.385%. The volatility measures have coefficient of variation (ratio of the standard deviation to the mean) close to 1, hence, a two-standard deviation change in market volatility can trigger the increase in average IVol by 25-75%. Higher market volatility predicts higher IVol for up to a year ahead, and vice versa.

Panel B repeats the analysis in Panel A replacing average idiosyncratic volatility with average analyst disagreement. The results are very similar: during recessions and after recessions, average analyst disagreement (measured as coefficient of variation of earnings forecasts) increases by roughly 20%, and a 1% increase in market volatility triggers a roughly 0.1-0.25% increase in average analyst disagreement (while a two-standard deviation, or 200%, increase in market volatility will increase average analyst disagreement by 20-50%).

Overall, the evidence in Table 13A is consistent with similar evidence presented by Barinov (2013), Bartram et al. (2016), Duarte et al. (2014), and Herskovic et al. (2016), all of whom find, using different measures and different sample periods, that idiosyncratic volatility increases in recessions and is positively correlated with systematic volatility.

9 Alternative Risk-Based Explanations

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

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

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

Adrian and Rosenberg (2008) use the Component GARCH (C-GARCH) model and divide C-GARCH forecast of market volatility into the short-run component (that mean-reverts fast) and long-run component (that mean-reverts extremely slowly). They find that both components are priced. Barinov (2018) performs the horse race between FVIX and the two volatility components as potential explanations of the maximum effect of Bali et al. (2011) and finds that FVIX is largely unrelated to shock to the long-run volatility component and the asset-pricing factor constructed from it, but has a strong overlap with shock to the short-run volatility component.

In Table 14A, I look at the overlap between FVIX and the two volatility components as factors explaining the distress risk puzzle. Panel A presents alphas of healthy-minus-distressed portfolios labeled according to the distress measure used to create the sorts (Cred, O-score, EDF). Other portfolios come from the double sorts on distress and disagreement/volatility/market-to-book in Tables 4 and 5 in the paper and Table 2A. For example, CredDispHI is a healthy-minus-distressed portfolio formed using only stocks in the top 30% on Disp (analyst disagreement), and CredIVolHI is a similar portfolio formed using only stocks in the top 30% in terms of idiosyncratic volatility. The other type of portfolios measures the difference in returns to the healthy-minus-distressed strategy between two groups of firms: for example, CredIVol measures this difference in the subsamples of top 30% and bottom 30% of firms in terms of idiosyncratic volatility.

The first two columns of Panel A present the CAPM and ICAPM alphas and thus repeat select results from Tables 2, 4 and 5 in the paper and Table 2A. The third column reports alphas from the Adrian-Rosenberg (2008) three-factor ICAPM, the three factors being the market portfolio and the factor-mimicking portfolios for changes in short-run and long-run volatility (SR and LR). All CAPM alphas but two are either significant or marginally significant at 10% level, with average alpha being 63 bp per month. ICAPM generates (absolute) average alpha of (15) 7 bp per month, and none of the alphas are significant. The Adrian-Rosenberg model produces average alpha of 50 bp - some improvement over CAPM, but far from the two-factor ICAPM with the market and FVIX.

A possible reason why the Adrian-Rosenberg model performs poorly is revealed in Panel B, which holds the volatility factor betas. The SR beta in column two, similar to the FVIX beta in column one, is negative and almost always significant, while the LR beta in column three is positive and significant, indicating that the positive-alpha portfolios are hedges against increases in long-run volatility (in contrast to what the model in McQuade, 2018, predicts). The LR betas are small, but since the LR factor premium is much larger than the SR factor premium, the positive LR betas can create an obstacle for the Adrian-Rosenberg ICAPM in explaining the distress risk puzzle and its cross-section.

A similar picture arises when I add FVIX to the Adrian-Rosenberg ICAPM: even with FVIX added, the average alpha of the anomalous portfolios is 30 bp per month, visibly larger than that in the two-factor ICAPM with the market and FVIX. Betas in Panel B also reveal overlap between FVIX and SR; compared to column one (two-factor ICAPM), FVIX beta drops by about one-third in the presence of SR, and compared to column two (Adrian-Rosenberg ICAPM), SR beta drops by roughly 20% in the presence of FVIX.

In the rest of Table 14A, I try dropping LR from the analysis, estimating a two-factor model with the market factor and SR and a three-factor model with the market, SR, and FVIX. The two-factor model still works significantly worse than the two-factor ICAPM with the market and FVIX used in the rest of the paper, but the deterioration of explanatory power when one uses SR instead of FVIX is expected: the market uses more information than C-GARCH does when estimating expected volatility (captured by VIX) and pricing index options.

Overall, Table 14A suggests that, in contrast to McQuade (2018) prediction, it is short-run rather than long-run market volatility that can potentially explain the distress risk puzzle, and FVIX has a significant overlap with the short-run volatility risk factor (SR), suggesting that VIX is just a cleaner proxy for expected short-run volatility than C-GARCH forecast (which is not surprising because investors are not limited to only information in the market index prices when they construct their best volatility forecast).

9.2 Distress Risk Puzzle in Conditional CAPM

O'Doherty (2012) shows that Conditional CAPM (CCAPM) can reduce the distress risk puzzle to statistically insignificant values (which remain economically sizeable at 35-50 bp per month). Following Boguth et al. (2011), O'Doherty (2012) suggests considering covariance between conditional market beta and market volatility in addition to controlling for the covariance between conditional market beta and expected market risk premium. That calls for the use of lagged market returns, historical portfolio betas, and VIX as extra conditioning variables, next to the traditional conditioning variables like default premium (yield spread between Baa and Aaa corporate bonds), dividend yield of the market portfolio, term spread, and short-term Treasury bill yield.[6]

The evidence in O'Doherty (2012) that the market beta of distressed firms is procyclical is consistent with one of the channels in my paper that link distress with FVIX exposures: if one couples the Johnson (2004) model (more uncertainty about assets makes beta of levered equity smaller) with the observation that firm-specific uncertainty is higher in recessions (when VIX is also higher), one can predict that betas of distressed firms are procyclical. My paper, however, takes several additional steps ahead compared to O'Doherty (2012): first, it considers the wealth effects of procyclical betas of distressed firms (i.e., smaller losses in bad times). Second, it links those wealth effects to a specific state variable (expected market volatility) and thus suggests adding a new factor and using ICAPM instead of CCAPM. Third, my paper generates cross-sectional predictions about the distress risk puzzle and its volatility risk explanation (see Tables 4 and 5 in the paper). Fourth, in Table 2 in the paper, the ICAPM makes the distress risk puzzle negative and insignificant rather than positive at 35-50 bp per month as in O'Doherty (2012).

Panel A of Table 15A repeats the analysis in O'Doherty (2012) using credit rating sorts instead of O-score and EDF sorts and comes to a very similar conclusion: the use of the four traditional conditioning variables or all seven conditioning variables (with lagged market returns, historical portfolio betas, and VIX added) reduces the alphas of distressed companies and the healthy-minus-distressed alpha differential to marginally significant values of 53 to 59 bp per month.

In Panel B and C of Table 15A, I add FVIX to the different versions of the CCAPM

[6]More detailed definition of the conditioning variables appears in online Data Appendix.

to gauge the overlap between the conditioning variables and FVIX. The overlap can serve as an estimate of the relative importance of the two channels in my explanation of the distress risk puzzle, one being the direct effect of higher volatility on the value of the option created by risky debt and the other being the effect of higher volatility on the beta of the said option. The overlap is also an estimate of my explanation's marginal contribution over O'Doherty (2012), who focuses solely on the second channel.

The first row of Panel B presents the alphas from the baseline ICAPM with the market factor and FVIX. The next three rows report very similar results, which suggests that, after I control for FVIX, making the market beta conditional does not add much towards explaining the distress risk puzzle. In other words, the second channel in my explanation of the distress risk puzzle, which drives the results of O'Doherty (2012), is significantly weaker than the first channel. Controlling for the conditioning variables changes the low-minus-high alpha by 1-12 bp per month (top line in Panel B vs. the second and fourth lines), whereas controlling for FVIX changed the low-minus-high alpha by full 80 bp per month (top line in Panel B vs. top line in Panel A).

Panel C reports the FVIX betas from the models in Panel B. Again, the panel starts with the FVIX betas from the baseline ICAPM without conditioning variables in the top row, and the subsequent rows show that the FVIX betas of distressed firms or the healthy-minus-distressed portfolio decrease by 12-20% in the presence of the conditioning variables. Thus, Panel C confirms that FVIX largely wins the horse race with the conditioning variables for the market beta.

Lastly, Table 16A reports , separately in expansions and recessions, the market betas of the healthy-minus-distressed (HMD) strategy in full sample (in the row labeled Cred), as well as betas of the HMD strategy in the top three IVol deciles (CredIVolHi row), the top three analyst disagreement deciles (CredDispHi row), and the top three market-to-book deciles (CredMBHi row), and the difference in betas of the HMD strategy between top and bottom three IVol/Disp/MB deciles (rows labeled CredIVol/CredDisp/CredMB).

One thing one can observe in Table 16A is that all market betas of the HMD strategy are negative, irrespective of the (sub)sample and whether the beta is measured in expansion or recession. Another thing is that these betas are almost always significantly less negative during recessions. The difference is economically sizeable: the change in spread in market betas between healthy and distressed firms, recession to expansion, is usually between 0.2 and 0.36, and can be as high as 0.59.[7]

The latter evidence is consistent with the extension of the Johnson model the paper presents: the risk of distressed firms decreases during recessions, and the risk of the HMD strategy correspondingly increases. However, the first piece of evidence (the market beta of HMD being significantly negative even in recessions) suggests that the explanatory power of the Johnson model/the Conditional CAPM with respect to the distress risk puzzle is limited (thus necessitating the use of FVIX to explain the distress risk puzzle): ideally, since the average raw return to HMD is non-negative, one would like to make the argument that the market beta of HMD only seems negative, because the static CAPM weighs periods by their length rather than their economic significance. If the beta of HMD is positive in recessions and negative in expansions, it will be negative in the static CAPM, since expansions tend to be much longer than recessions, but the Conditional CAPM will weigh periods properly, using expected market risk premium as the weight, and the weighted average conditional beta of HMD will be close to zero, consistent with

[7] CredDispHi has slightly less procyclical beta than Cred, because Cred is formed in a broader sample, which includes firms not covered by analysts or covered by just one analyst, whereas CredDispHi is formed in the sample of firms covered by at least two analysts, so that the analyst disagreement measure was available.

insignificantly positive average raw return to HMD. Yet, as Table 16A shows, we never really see a positive market beta of HMD during recessions.

9.3 Distress Risk Puzzle in Conditional ICAPM

Taken at the face value, the empirical ICAPM in the paper assumes that the reaction to the volatility shock does not depend on the level of volatility that preceded the shock (FVIX is tracking $VIX_t - VIX_{t-1}$, not a percentage change in VIX). Propositions 2 and 3 in the paper focus on elasticities, that is, beta/firm return reaction to a percentage shock in volatility, so their implicit assumption is that the same absolute shock to volatility would matter less in a more volatile environment (because the shock would be smaller in percentage terms).

A potential dependence of volatility shock importance on the level of volatility is an interesting question, and I can see the effect going both ways: maybe a fixed volatility shock would be less influential in volatile times (because it is a smaller percentage of the existing volatility level) or maybe a fixed volatility shock would be less influential in low-volatility periods, as the business environment is more stable and firms are less likely to be pushed towards bankruptcy. Table 17A explore the implications of the size of volatility shock for my research question, that is, for explaining the alphas of the healthy-minus-distressed (HMD) strategy.

Table 17A makes FVIX beta conditional on the four standard business cycle variables commonly used in the Conditional CAPM (default premium, dividend yield, Treasury bill yield, and term spread). The main point is to see whether the HMD strategy is more responsive or less responsive to volatility shocks in different states of the economy. Panel A1 splits the sample into recessions and expansions the traditional for the conditional models way: recessions/expansions are defined as periods when expected market risk premium is above/below the in-sample mean. Expected market risk premium is the fitted value from the predictive regression that predicts the market return using the four conditioning variables:

$$MKT_t - RF_t = c_0 + c_1 \cdot DEF_{t-1} + c_1 \cdot DIV_{t-1} + c_3 \cdot TB_{t-1} + c_4 \cdot TERM_{t-1} \qquad (2)$$

Panel A2 splits the sample by looking at expected FVIX return instead (since FVIX is countercyclical by construction, its risk premium during recessions is more negative than during expansions). Expected FVIX return is the fitted value from

$$FVIX_t = c_0 + c_1 \cdot DEF_{t-1} + c_1 \cdot DIV_{t-1} + c_3 \cdot TB_{t-1} + c_4 \cdot TERM_{t-1} \qquad (3)$$

Panel A3 splits the sample based directly on value of VIX in the previous month. Panel B of Table 17A reports full-sample alphas from the CAPM, the ICAPM, and the Conditional CAPM.

The test assets in Table 17A are the same arbitrage portfolios as in Table 16A (HMD strategies in the full sample, in volatile/growth subsamples). Panel A of Table 17A reveals that for all expansion/recessions splits and in all subsamples, the HMD strategy loads more negatively on FVIX (has higher volatility risk) in recessions than in expansions. The increase in the magnitude of FVIX beta is, in most cases, 15-30% (statistically significant for all but one portfolios). I conclude that a fixed volatility shock matters more during recessions, but also observe, based on the small difference in the alphas between ICAPM and the Conditional ICAPM in Panel B, that this effect is unlikely to be economically important – making the FVIX beta conditional and accounting for the fact that HMD responsiveness to volatility changes varies between low- and high-volatility periods only changes the alpha of HMD by at most 10 bp per month.

In untabulated results, I also use alternative conditioning variables: I use VIX as the only conditioning variable and I add VIX (along with lagged market risk premium) to the four commonly used conditioning variables from Table 17A. The results are similar: FVIX beta of HMD is more negative in recessions, but controlling for that changes the alpha of HMD by at most 10 bp per month.

10 CRSP Breakpoints and No Price Screen

Table 18A checks the robustness of my findings in one more way, by going back to credit rating quintile sorts, but performing them using CRSP breakpoints instead of NYSE breakpoints and without filtering out stocks priced below $5 per share at the portfolio formation date. That way the worst credit rating quintile is more likely to include smaller, more severely distressed firms. The downside is a potential loss of power due to noise in returns to penny stocks and issues with tradeability of the HMD strategy.

The reason to look at more extremely distressed firms is two-fold. First, one can expect the distress risk puzzle to be mechanically stronger and tougher to explain if the distressed firms quintile holds more severely distressed firms. Second, based on the facts that the argument in the paper seems similar to "at the money options have the highest vega" and that the simulations of derivatives in Proposition 3 do show that the derivatives suggesting positive loadings of distressed firms on FVIX do decline somewhat for firms with extremely high leverage, one can surmise that the distress risk puzzle for extremely distressed firms can flip its sign (that is, very distressed firms will have higher, not lower returns than simply distressed firms)/

Comparing Table 18A to Table 2 in the paper I find that the distress risk puzzle is a bit stronger in Table 18A - for example, value-weighted spread in CAPM alphas between the best and worst credit rating quintile is 83 bp in Panel A of Table 2 vs. 93 bp in Panel A of Table 18A. There are no visible issues with the distress risk puzzle flipping its sign for extremely distressed firms: the alphas of the worst credit rating quintile in Table 18A are generally larger than in Table 2 in the paper (Carhart alphas are an exception, but they are quite close and quite noisy both in Table 18A and Table 2 in the paper). The significant FVIX beta differential between healthy and distressed firms is also preserved in Table 18A, and FVIX betas of the worst credit rating quintile are similar to or larger than respective FVIX betas in Table 2 in the paper. I also find that Table 18A preserves a highly significant FVIX beta spread between distressed and healthy firms, as well as the ability of FVIX to largely explain the distress risk puzzle.

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Table 1A. Alternative Measures of Distress

The table reports alphas from the CAPM, the Fama-French model (FF), and the Carhart model, as well as alphas and FVIX betas from the two-factor ICAPM with the market factor and FVIX, the four-factor model with the three Fama-French factors and FVIX (FF4), and the five-factor model (the Carhart model augmented with FVIX, "5factor"). The models are fitted to the quintile portfolios sorted on O-score (Panel A) and expected default frequency, EDF (Panel B). The quintiles are formed using NYSE (exchcd=1) breakpoints and are rebalanced annually. FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Panel A. O-Score Quintiles

A1. CAPM as Benchmark Model

	Low	**O2**	**O3**	**O4**	**High**	**L-H**
$\boldsymbol{\alpha}_{CAPM}$	0.025	0.209	0.143	0.205	-0.244	0.270
t-stat	*0.24*	*2.92*	*1.35*	*1.92*	*-1.99*	*1.60*
$\boldsymbol{\alpha}_{ICAPM}$	0.068	0.033	0.079	0.158	0.056	0.012
t-stat	*0.67*	*0.47*	*0.79*	*1.30*	*0.40*	*0.07*
$\boldsymbol{\beta}_{FVIX}$	0.092	-0.381	-0.138	-0.101	0.649	-0.556
t-stat	*0.94*	*-3.40*	*-1.28*	*-0.98*	*5.74*	*-4.04*

Panel B. EDF Quintiles

B1. CAPM as Benchmark Model

	Low	**EDF2**	**EDF3**	**EDF4**	**High**	**L-H**
$\boldsymbol{\alpha}_{CAPM}$	0.116	0.128	0.337	-0.004	-0.083	0.198
t-stat	*1.19*	*1.80*	*2.28*	*-0.02*	*-0.39*	*0.78*
$\boldsymbol{\alpha}_{ICAPM}$	-0.102	0.059	0.228	0.058	0.044	-0.146
t-stat	*-1.09*	*0.67*	*1.65*	*0.35*	*0.20*	*-0.56*
$\boldsymbol{\beta}_{FVIX}$	-0.471	-0.150	-0.236	0.132	0.273	-0.744
t-stat	*-4.70*	*-1.22*	*-1.02*	*0.59*	*1.34*	*-4.33*

A2. Fama-French Model as Benchmark Model

	Low	O2	O3	O4	High	L-H
$\boldsymbol{\alpha}_{FF}$	0.189	0.148	0.071	0.154	-0.411	0.600
t-stat	*2.11*	*2.70*	*0.85*	*1.61*	*-2.70*	*3.18*
$\boldsymbol{\alpha}_{FF4}$	0.150	0.049	0.042	0.076	-0.116	0.266
t-stat	*1.90*	*0.73*	*0.46*	*0.64*	*-0.97*	*1.88*
$\boldsymbol{\beta}_{FVIX}$	0.035	-0.325	-0.159	-0.183	0.300	-0.266
t-stat	*0.45*	*-3.13*	*-1.60*	*-1.98*	*2.88*	*-2.16*

B2. Fama-French Model as Benchmark Model

	Low	EDF2	EDF3	EDF4	High	L-H
$\boldsymbol{\alpha}_{FF}$	0.144	0.103	0.282	-0.097	-0.260	0.403
t-stat	*1.63*	*1.42*	*2.15*	*-0.69*	*-1.53*	*2.01*
$\boldsymbol{\alpha}_{FF4}$	-0.024	0.073	0.168	-0.056	-0.176	0.152
t-stat	*-0.29*	*0.93*	*1.30*	*-0.38*	*-1.05*	*0.80*
$\boldsymbol{\beta}_{FVIX}$	-0.382	-0.068	-0.259	0.095	0.191	-0.573
t-stat	*-3.28*	*-1.03*	*-1.30*	*0.55*	*1.33*	*-3.22*

A3. Carhart Model as Benchmark Model

	Low	O2	O3	O4	High	L-H
$\boldsymbol{\alpha}_{Carhart}$	0.239	0.150	0.045	0.050	-0.209	0.449
t-stat	*3.44*	*2.88*	*0.69*	*0.54*	*-1.76*	*3.21*
$\boldsymbol{\alpha}_{5factor}$	0.212	0.077	0.088	0.120	0.051	0.161
t-stat	*2.40*	*1.15*	*1.01*	*1.15*	*0.38*	*1.04*
$\boldsymbol{\beta}_{FVIX}$	0.041	-0.322	-0.155	-0.179	0.316	-0.276
t-stat	*0.58*	*-3.18*	*-1.59*	*-2.05*	*3.54*	*-2.23*

B3. Carhart Model as Benchmark Model

	Low	EDF2	EDF3	EDF4	High	L-H
$\boldsymbol{\alpha}_{Carhart}$	0.251	0.181	0.133	0.025	-0.015	0.266
t-stat	*4.40*	*3.16*	*2.00*	*0.35*	*-0.15*	*2.37*
$\boldsymbol{\alpha}_{5factor}$	0.126	0.131	0.070	0.068	0.134	-0.008
t-stat	*1.62*	*1.79*	*0.90*	*0.85*	*1.05*	*-0.06*
$\boldsymbol{\beta}_{FVIX}$	-0.149	-0.063	-0.032	0.120	0.296	-0.445
t-stat	*-1.41*	*-0.60*	*-0.33*	*1.38*	*2.52*	*-4.10*

Table 2A. Distress Risk Puzzle, Analyst Disagreement, and Aggregate Volatility Risk

Panel A presents CAPM alphas, ICAPM alphas, and FVIX betas for the conditional double sorts first into three groups (bottom 30%, middle 40%, top 30%) on analyst disagreement and then into quintiles on credit rating. The double sorts are repeated each month and use NYSE (exchcd=1) quintiles. Analyst disagreement is the standard deviation of earnings-per-share forecasts for the current fiscal year (from IBES) scaled by their absolute average value. Panel B presents the Carhart alphas, the 5-factor alphas (from the Carhart model augmented with FVIX), and FVIX betas of the same double-sorted portfolios. FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. Panel C reports average credit rating (coded as AAA=1, AA+=2, ... D=22), and Panel D reports average number of firms in each of the double sorted portfolios. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017. 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	0.386	0.332	0.366	0.019
t-stat	*2.99*	*2.67*	*1.79*	*0.09*
Cred2	0.346	0.191	0.122	0.252
t-stat	*2.09*	*1.12*	*0.45*	*1.02*
Cred3	0.472	0.435	0.183	0.289
t-stat	*2.88*	*2.09*	*0.58*	*1.15*
Cred4	0.334	0.139	-0.121	0.452
t-stat	*1.58*	*0.63*	*-0.42*	*1.80*
Worst	0.289	0.225	-0.503	0.792
t-stat	*1.20*	*0.88*	*-1.42*	*2.08*
B-W	0.097	0.107	0.869	0.772
t-stat	*0.39*	*0.44*	*2.49*	*2.02*

Panel A2. ICAPM alphas

	Low	**Med**	**High**	**L-H**
Best	0.031	0.144	0.253	-0.222
t-stat	*0.24*	*1.03*	*1.12*	*-0.95*
Cred2	0.107	0.141	0.156	-0.028
t-stat	*0.69*	*0.84*	*0.53*	*-0.11*
Cred3	0.167	0.382	0.322	-0.155
t-stat	*0.99*	*1.82*	*1.03*	*-0.62*
Cred4	0.237	0.142	0.042	0.186
t-stat	*0.99*	*0.61*	*0.14*	*0.67*
Worst	0.439	0.685	0.184	0.255
t-stat	*1.60*	*2.40*	*0.48*	*0.63*
B-W	-0.408	-0.541	0.069	0.477
t-stat	*-1.41*	*-2.02*	*0.19*	*1.13*

Panel A3. FVIX Betas

	Low	**Med**	**High**	**L-H**
Best	-0.727	-0.386	-0.233	-0.495
t-stat	*-3.85*	*-1.98*	*-0.77*	*-2.21*
Cred2	-0.495	-0.103	0.071	-0.581
t-stat	*-2.33*	*-0.58*	*0.19*	*-2.65*
Cred3	-0.627	-0.109	0.285	-0.911
t-stat	*-2.59*	*-0.51*	*0.87*	*-4.58*
Cred4	-0.201	0.006	0.329	-0.535
t-stat	*-0.89*	*0.03*	*1.47*	*-3.11*
Worst	0.309	0.943	1.409	-1.100
t-stat	*1.86*	*5.60*	*5.36*	*-3.63*
B-W	-1.037	-1.329	-1.642	-0.605
t-stat	*-4.83*	*-6.24*	*-4.06*	*-1.62*

Panel B1. Carhart alphas

	Low	Med	High	L-H
Best	0.365	0.308	0.341	0.024
t-stat	*3.18*	*3.05*	*2.21*	*0.14*
Cred2	0.269	0.115	0.083	0.204
t-stat	*1.90*	*0.90*	*0.40*	*0.90*
Cred3	0.421	0.337	0.163	0.258
t-stat	*2.84*	*2.22*	*0.67*	*1.13*
Cred4	0.275	0.138	-0.132	0.406
t-stat	*1.49*	*0.80*	*-0.57*	*1.50*
Worst	0.262	0.434	-0.211	0.472
t-stat	*1.41*	*2.53*	*-0.71*	*1.25*
B-W	0.103	-0.126	0.551	0.448
t-stat	*0.58*	*-0.74*	*1.77*	*1.29*

Panel B2. 5-factor alphas

	Low	Med	High	L-H
Best	0.113	0.159	0.235	-0.122
t-stat	*1.08*	*1.56*	*1.45*	*-0.70*
Cred2	0.080	0.038	0.076	0.012
t-stat	*0.63*	*0.28*	*0.35*	*0.05*
Cred3	0.109	0.220	0.158	-0.049
t-stat	*0.81*	*1.52*	*0.75*	*-0.23*
Cred4	0.081	-0.009	-0.146	0.222
t-stat	*0.41*	*-0.06*	*-0.65*	*0.78*
Worst	0.198	0.577	0.147	0.051
t-stat	*0.95*	*3.36*	*0.48*	*0.13*
B-W	-0.085	-0.418	0.088	0.173
t-stat	*-0.41*	*-2.44*	*0.28*	*0.44*

Panel B3. FVIX Betas

	Low	Med	High	L-H
Best	-0.529	-0.311	-0.221	-0.307
t-stat	*-3.31*	*-3.47*	*-1.68*	*-1.53*
Cred2	-0.402	-0.163	-0.015	-0.408
t-stat	*-2.61*	*-1.74*	*-0.09*	*-2.69*
Cred3	-0.655	-0.245	-0.011	-0.644
t-stat	*-3.72*	*-1.84*	*-0.06*	*-3.54*
Cred4	-0.407	-0.308	-0.030	-0.379
t-stat	*-2.45*	*-2.14*	*-0.19*	*-1.97*
Worst	-0.133	0.301	0.751	-0.884
t-stat	*-0.81*	*1.95*	*3.88*	*-3.32*
B-W	-0.395	-0.612	-0.972	-0.577
t-stat	*-1.68*	*-3.55*	*-4.80*	*-2.05*

Panel C. Average Credit Rating

	Low	Med	High	H-L	Full
Best	3.8	5.3	7.4	3.6	5.1
Cred2	6.4	8.0	10.1	3.7	8.1
Cred3	8.0	9.6	11.9	3.9	10.1
Cred4	9.8	11.3	13.5	3.7	12.1
Worst	12.8	13.6	15.3	2.6	14.4
W-B	9.0	8.3	8.0	-1.0	9.3
t-stat	*79.5*	*109.7*	*74.2*	*-10.1*	*92.5*

Panel D. Average Number of Observations

	Low	Med	High	H-L	Full
Best	37.1	50.7	37.3	0.2	151.9
Cred2	28.4	41.7	30.5	2.1	143.7
Cred3	27.5	38.5	35.0	7.4	124.9
Cred4	28.3	41.0	42.9	14.6	136.9
Worst	34.6	49.2	34.2	-0.4	189.2
W-B	-2.4	-1.5	-3.0	-0.6	37.2
t-stat	*-2.73*	*-0.80*	*-2.06*	*-0.44*	*6.53*

Table 3A. O-Score, Market-to-Book, and Aggregate Volatility Risk

Panel A presents CAPM alphas, ICAPM alphas, and FVIX betas for the conditional double sorts first into three groups (bottom 30%, middle 40%, top 30%) on market-to-book and then into quintiles on O-score (inverse logistic transformation of estimated probability of bankruptcy). The double sorts on are repeated each year and use NYSE (exchcd=1) quintiles. Panel B presents the Carhart alphas, the 5-factor alphas (from the Carhart model augmented with FVIX), and FVIX betas of the same double-sorted portfolios. FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. Panel C reports average credit rating (coded as AAA=1, AA+=2, ... D=22), and Panel D reports average number of firms in each of the double sorted portfolios. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017. 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
Low	0.465	0.109	-0.021	0.486
t-stat	*3.30*	*0.90*	*-0.18*	*2.32*
O2	0.366	0.134	0.015	0.351
t-stat	*2.52*	*1.31*	*0.16*	*1.85*
O3	0.397	0.104	0.016	0.381
t-stat	*2.54*	*0.94*	*0.19*	*2.04*
O4	0.410	0.168	-0.065	0.475
t-stat	*2.42*	*1.70*	*-0.72*	*2.64*
High	0.511	0.037	-0.412	0.923
t-stat	*2.82*	*0.23*	*-2.63*	*4.00*
L-H	-0.046	0.072	0.391	0.437
t-stat	*-0.22*	*0.33*	*2.11*	*1.75*

Panel A2. ICAPM alphas

	Value	Neut	Growth	G-V
Low	0.437	0.064	0.026	0.411
t-stat	*2.05*	*0.32*	*0.15*	*1.37*
O2	0.119	0.165	0.082	0.037
t-stat	*0.56*	*1.21*	*0.71*	*0.14*
O3	0.419	-0.098	0.124	0.295
t-stat	*1.80*	*-0.58*	*1.15*	*1.23*
O4	0.383	0.064	0.055	0.328
t-stat	*1.45*	*0.36*	*0.57*	*1.25*
High	0.289	-0.080	0.102	0.187
t-stat	*1.11*	*-0.33*	*0.48*	*0.53*
L-H	0.148	0.144	-0.076	-0.224
t-stat	*0.50*	*0.49*	*-0.32*	*-0.64*

Panel A3. FVIX Betas

	Value	Neut	Growth	G-V
Low	-0.030	0.011	0.183	-0.213
t-stat	*-0.15*	*0.06*	*1.34*	*-0.79*
O2	-0.102	-0.482	-0.209	0.107
t-stat	*-0.49*	*-3.04*	*-2.66*	*0.52*
O3	0.280	-0.405	-0.216	0.496
t-stat	*1.08*	*-1.82*	*-2.19*	*2.50*
O4	0.082	-0.130	-0.106	0.188
t-stat	*0.28*	*-0.55*	*-1.31*	*0.77*
High	0.035	0.266	1.128	-1.093
t-stat	*0.13*	*1.25*	*2.77*	*-1.70*
L-H	-0.065	-0.255	-0.945	-0.880
t-stat	*-0.28*	*-1.22*	*-2.72*	*-1.83*

Panel B1. Carhart alphas

	Value	Neut	Growth	G-V
Low	0.407	0.266	0.309	0.098
t-stat	*2.71*	*2.05*	*2.89*	*0.53*
O2	0.217	0.091	0.160	0.056
t-stat	*1.96*	*0.89*	*2.02*	*0.41*
O3	0.197	0.018	0.181	0.016
t-stat	*1.76*	*0.17*	*2.35*	*0.12*
O4	0.276	0.044	-0.022	0.298
t-stat	*2.04*	*0.49*	*-0.21*	*2.17*
High	0.324	-0.115	-0.293	0.617
t-stat	*2.11*	*-0.83*	*-2.32*	*3.10*
L-H	0.083	0.382	0.602	0.518
t-stat	*0.36*	*1.77*	*3.44*	*1.90*

Panel B2. 5-factor alphas

	Value	Neut	Growth	G-V
Low	0.499	0.267	0.266	0.232
t-stat	*2.34*	*1.34*	*1.87*	*0.89*
O2	0.085	0.168	0.145	-0.060
t-stat	*0.55*	*1.41*	*1.45*	*-0.32*
O3	0.289	-0.096	0.207	0.082
t-stat	*1.72*	*-0.68*	*1.97*	*0.47*
O4	0.346	-0.014	0.004	0.343
t-stat	*1.89*	*-0.11*	*0.03*	*1.98*
High	0.214	-0.203	-0.077	0.290
t-stat	*1.02*	*-1.02*	*-0.55*	*1.10*
L-H	0.285	0.470	0.343	0.058
t-stat	*0.90*	*1.58*	*2.08*	*0.16*

Panel B3. FVIX Betas

	Value	Neut	Growth	G-V
Low	-0.030	-0.016	0.082	-0.112
t-stat	*-0.18*	*-0.09*	*0.75*	*-0.66*
O2	-0.117	-0.401	-0.189	0.072
t-stat	*-1.13*	*-4.50*	*-1.56*	*0.60*
O3	0.159	-0.337	-0.221	0.381
t-stat	*0.89*	*-2.68*	*-1.86*	*2.62*
O4	-0.018	-0.170	-0.172	0.154
t-stat	*-0.12*	*-1.26*	*-1.55*	*1.09*
High	-0.144	0.050	0.460	-0.604
t-stat	*-0.95*	*0.29*	*2.67*	*-2.78*
L-H	0.114	-0.066	-0.378	-0.492
t-stat	*0.47*	*-0.31*	*-1.61*	*-1.96*

Panel C. Average O-Score

	Value	Neut	Growth	V-G	Full
Low	-4.42	-4.75	-5.37	-0.95	-4.86
O2	-2.59	-2.60	-2.61	-0.02	-2.60
O3	-1.75	-1.77	-1.76	-0.01	-1.76
O4	-0.97	-0.98	-0.97	-0.01	-0.98
High	0.52	0.98	2.66	2.14	1.59
H-L	4.94	5.73	8.03	3.09	6.45
t-stat	*163.2*	*76.3*	*30.2*	*11.7*	*48.7*

Panel D. Average Number of Observations

	Value	Neut	Growth	V-G	Full
Low	165.9	223.0	217.3	51.4	623.6
O2	113.2	144.0	132.5	19.4	397.5
O3	107.6	133.9	115.6	8.03	369.4
O4	117.6	134.7	126.1	8.53	389.5
High	149.6	206.6	264.6	115.0	646.3
H-L	-16.3	-16.3	47.3	63.6	22.7
t-stat	*-4.54*	*-3.70*	*7.69*	*10.79*	*1.88*

Table 4A. Distress Risk Puzzle and Downgrades

The table reports the CAPM alphas and the ICAPM alphas, as well as the FVIX betas of the credit rating quintiles with some months around portfolio formation (named in the panel headers) omitted from the sample. Time t is the portfolio formation month, time *t-6* (*t+6*) is six months prior to (after) portfolio formation. I define a month with a downgrade as a month in which the credit rating becomes worse than in the previous month. Panel A, for example, excludes from the sample all stocks that had at least one downgrade month any time between six months prior to the portfolio formation and six months after portfolio formation.

Panel A. No Downgrades in t-6 to t+6

	Best	**Cred2**	**Cred3**	**Cred4**	**Worst**	**B-W**
	A+	*BBB+*	*BBB-*	*BB*	*B+*	
$\boldsymbol{\alpha}_{Carhart}$	0.321	0.299	0.292	0.151	0.107	0.214
t-stat	*4.09*	*3.00*	*2.25*	*1.10*	*1.04*	*1.74*
$\boldsymbol{\alpha}_{5factor}$	0.136	0.157	0.142	0.031	0.207	-0.070
t-stat	*2.02*	*1.75*	*1.19*	*0.23*	*2.05*	*-0.68*
$\boldsymbol{\beta}_{FVIX}$	-0.406	-0.314	-0.330	-0.265	0.220	-0.626
t-stat	*-3.82*	*-3.27*	*-2.45*	*-1.78*	*1.93*	*-4.56*

Panel B. No Downgrades in t-6 to t

	Best	**Cred2**	**Cred3**	**Cred4**	**Worst**	**B-W**
Rating	*A+*	*BBB+*	*BBB-*	*BB*	*B+*	
$\boldsymbol{\alpha}_{Carhart}$	0.287	0.223	0.231	-0.001	-0.217	0.503
t-stat	*3.78*	*2.44*	*1.83*	*0.00*	*-1.91*	*3.53*
$\boldsymbol{\alpha}_{5factor}$	0.105	0.098	0.097	-0.113	-0.065	0.170
t-stat	*1.57*	*1.16*	*0.83*	*-0.89*	*-0.66*	*1.60*
$\boldsymbol{\beta}_{FVIX}$	-0.401	-0.274	-0.293	-0.248	0.334	-0.735
t-stat	*-3.87*	*-3.05*	*-2.34*	*-1.63*	*2.48*	*-4.86*

Panel C. Only Downgrades in t-6 to t

	Best	**Cred2**	**Cred3**	**Cred4**	**Worst**	**B-W**
	A+	*BBB+*	*BBB-*	*BB*	*B+*	
$\boldsymbol{\alpha}_{Carhart}$	0.009	0.491	-0.214	0.570	-0.549	0.554
t-stat	*0.04*	*2.10*	*-0.82*	*1.68*	*-1.32*	*1.08*
$\boldsymbol{\alpha}_{5factor}$	-0.156	0.358	0.009	0.755	-0.241	0.060
t-stat	*-0.56*	*1.51*	*0.04*	*2.30*	*-0.59*	*0.12*
$\boldsymbol{\beta}_{FVIX}$	-0.354	-0.296	0.490	0.399	0.678	-1.057
t-stat	*-2.05*	*-1.24*	*2.11*	*1.55*	*1.93*	*-2.78*

Panel D. No Downgrades in t to t+6

	Best	**Cred2**	**Cred3**	**Cred4**	**Worst**	**B-W**
Rating	*A+*	*BBB+*	*BBB-*	*BB*	*B+*	
$\boldsymbol{\alpha}_{Carhart}$	0.321	0.321	0.323	0.215	0.184	0.137
t-stat	*4.06*	*3.26*	*2.44*	*1.57*	*1.85*	*1.14*
$\boldsymbol{\alpha}_{5factor}$	0.138	0.180	0.180	0.102	0.284	-0.146
t-stat	*2.03*	*2.03*	*1.51*	*0.78*	*2.85*	*-1.44*
$\boldsymbol{\beta}_{FVIX}$	-0.404	-0.309	-0.316	-0.249	0.220	-0.624
t-stat	*-3.92*	*-3.40*	*-2.46*	*-1.79*	*1.99*	*-4.11*

Table 5A. Distress Risk Puzzle and Funds from Operations

The table reports alphas from the CAPM and the Carhart model, as well as alphas and FVIX betas from the two-factor ICAPM with the market factor and FVIX and the five-factor model (the Carhart model augmented with FVIX, "5factor"). The models are fitted to the quintile portfolios sorted on funds from operations divided by total assets (FFO, Panel A), O-score (Panel B), and credit rating (Panel C). The sorts on Panel B and C are conditional on FFO: firms are first sorted in FFO quintiles and then, within each FFO quintile, on O-score or credit rating. The quintiles are formed using NYSE (exchcd=1) breakpoints. O-score and FFO quintiles are rebalanced annually, credit rating quintiles are rebalanced monthly. FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. Detailed definitions of all variables are in online Data Appendix. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Panel A. Sorts on Funds from Operations (FFO)

	Low	**FFO2**	**FFO3**	**FFO4**	**High**	**H-L**
$\boldsymbol{\alpha}_{CAPM}$	-0.375	-0.051	0.231	0.184	0.071	0.446
t-stat	*-2.92*	*-0.54*	*2.74*	*2.44*	*0.64*	*2.83*
$\boldsymbol{\alpha}_{ICAPM}$	0.008	-0.047	0.040	0.034	0.159	0.151
t-stat	*0.07*	*-0.45*	*0.45*	*0.46*	*1.46*	*1.01*
$\boldsymbol{\beta}_{FVIX}$	0.828	0.009	-0.414	-0.323	0.191	-0.638
t-stat	*4.78*	*0.08*	*-3.71*	*-2.83*	*1.64*	*-5.68*
$\boldsymbol{\alpha}_{Carhart}$	-0.240	0.016	0.271	0.165	0.235	0.475
t-stat	*-1.75*	*0.16*	*3.21*	*2.37*	*2.85*	*2.97*
$\boldsymbol{\alpha}_{5factor}$	0.049	-0.001	0.109	0.049	0.259	0.210
t-stat	*0.43*	*-0.01*	*1.33*	*0.67*	*3.14*	*1.56*
$\boldsymbol{\beta}_{FVIX}$	0.652	-0.037	-0.364	-0.262	0.055	-0.597
t-stat	*4.71*	*-0.33*	*-4.38*	*-2.23*	*0.84*	*-3.63*

Panel B. Sorts on O-score, Conditional on FFO

	Low	O2	O3	O4	High	L-H
$\boldsymbol{\alpha}_{CAPM}$	-0.020	0.160	0.150	0.148	-0.015	-0.004
t-stat	*-0.18*	*2.20*	*1.84*	*1.46*	*-0.14*	*-0.03*
$\boldsymbol{\alpha}_{Carhart}$	0.166	0.180	0.142	0.173	0.078	0.088
t-stat	*1.91*	*2.41*	*1.81*	*1.91*	*0.70*	*0.66*
$\boldsymbol{\alpha}_{5factor}$	0.226	0.112	0.071	0.079	0.157	0.068
t-stat	*2.50*	*1.45*	*0.93*	*0.81*	*1.56*	*0.54*
$\boldsymbol{\beta}_{FVIX}$	0.134	-0.154	-0.161	-0.213	0.179	-0.045
t-stat	*1.31*	*-1.78*	*-1.30*	*-1.31*	*1.63*	*-0.31*

Panel C. Sorts on Credit Rating, Conditional on FFO

	A	*BBB+*	*BBB-*	*BB*	*B+*	
	Best	**Cred2**	**Cred3**	**Cred4**	**Worst**	**B-W**
$\boldsymbol{\alpha}_{CAPM}$	0.295	0.232	0.157	0.059	-0.305	0.600
t-stat	*2.61*	*1.47*	*0.89*	*0.31*	*-1.55*	*2.89*
$\boldsymbol{\alpha}_{Carhart}$	0.270	0.198	0.101	0.055	-0.128	0.397
t-stat	*3.65*	*1.76*	*0.94*	*0.42*	*-1.10*	*2.90*
$\boldsymbol{\alpha}_{5factor}$	0.115	0.086	-0.014	0.031	-0.018	0.133
t-stat	*1.68*	*0.87*	*-0.13*	*0.24*	*-0.16*	*1.09*
$\boldsymbol{\beta}_{FVIX}$	-0.343	-0.249	-0.255	-0.054	0.244	-0.586
t-stat	*-4.23*	*-2.09*	*-1.88*	*-0.35*	*1.92*	*-3.84*

Table 6A. Alternative FVIX Factors

Panel A presents correlations between monthly change in VIX (Δ VIX) and four versions of the FVIX factor - FVIX, with volatility sensitivity quintiles as base assets (the one used in the paper); FVIX6, with two-by-three size/market-to-book sorts as base assets; FVIXind, with ten industry portfolios from Fama and French (1997) as base assets; FVIXT, with the same base assets as FVIX, but from the factor-mimicking regression estimated using expanding window; FVIXtr, with base assets purged of firms with missing credit rating or with credit rating in the worst quintile. Panel B reports descriptive statistics, including the Sharpe ratio (mean over standard deviation) and appraisal ratio (alpha over idiosyncratic volatility) for the same four versions of FVIX. Panels C to F present alphas and betas of the four FVIX versions. Alphas and betas are coming from the CAPM, the three factor Fama and French (1993) model, the Carhart (1997) model, the five-factor Fama and French (2015) model, and the five-factor Fama-French model augmented with Carhart's momentum factor. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

Panel A. Correlations

	ΔVIX	FVIX	FVIX6	FVIXind	FVIXT	FVIXtrC
ΔVIX	1	0.676	0.653	0.676	0.738	0.673
FVIX	0.676	1	0.980	0.981	0.991	0.982
FVIX6	0.653	0.980	1	0.976	0.968	0.975
FVIXind	0.676	0.981	0.976	1	0.974	0.984
FVIXT	0.738	0.991	0.968	0.974	1	0.978
FVIXtrC	0.673	0.982	0.975	0.984	0.978	1

Panel B. Descriptive Statistics

	Mean	StDev	Sharpe	CAPM alpha	Appraisal	Skew
FVIX	-1.366	5.978	-0.229	-0.463	-0.337	1.003
FVIX6	-1.245	6.008	-0.207	-0.347	-0.207	0.795
FVIXind	-1.385	6.217	-0.223	-0.448	-0.297	0.950
FVIXT	-1.143	4.518	-0.253	-0.381	-0.398	0.630
FVIXtr	-1.347	6.231	-0.216	-0.467	-0.307	0.815

Panel C. Alphas and Betas of Baseline FVIX

	Raw	CAPM	FF	Carhart	FF5	FF6
$\boldsymbol{\alpha}$	-1.366	-0.463	-0.439	-0.444	-0.305	-0.319
t-stat	*-4.77*	*-4.73*	*-4.00*	*-3.91*	*-3.73*	*-3.80*
$\boldsymbol{\beta}_{MKT}$		-1.325	-1.358	-1.357	-1.407	-1.403
t-stat		*-37.0*	*-35.2*	*-34.0*	*-50.7*	*-49.2*
$\boldsymbol{\beta}_{SMB}$			0.170	0.170	0.107	0.104
t-stat			*4.94*	*5.08*	*4.56*	*4.70*
$\boldsymbol{\beta}_{HML}$			-0.073	-0.070	0.034	0.053
t-stat			*-1.41*	*-1.41*	*0.59*	*0.86*
$\boldsymbol{\beta}_{CMA}$					-0.142	-0.156
t-stat					*-2.31*	*-2.50*
$\boldsymbol{\beta}_{RMW}$					-0.224	-0.232
t-stat					*-6.15*	*-6.31*
$\boldsymbol{\beta}_{MOM}$				0.006		0.028
t-stat				*0.35*		*1.57*

Panel D. Alphas and Betas of FVIX6 (Size/MB-based)

	Raw	CAPM	FF	Carhart	FF5	FF6
$\boldsymbol{\alpha}$	-1.245	-0.347	-0.318	-0.339	-0.168	-0.195
t-stat	*-4.31*	*-3.74*	*-3.41*	*-3.71*	*-2.51*	*-3.06*
$\boldsymbol{\beta}_{MKT}$		-1.316	-1.381	-1.375	-1.437	-1.429
t-stat		*-38.7*	*-44.4*	*-44.1*	*-61.1*	*-62.3*
$\boldsymbol{\beta}_{SMB}$			0.397	0.396	0.322	0.317
t-stat			*8.38*	*9.00*	*11.48*	*12.74*
$\boldsymbol{\beta}_{HML}$			-0.091	-0.080	0.028	0.062
t-stat			*-1.40*	*-1.27*	*0.53*	*1.24*
$\boldsymbol{\beta}_{CMA}$					-0.153	-0.178
t-stat					*-2.84*	*-3.42*
$\boldsymbol{\beta}_{RMW}$					-0.261	-0.275
t-stat					*-7.83*	*-9.19*
$\boldsymbol{\beta}_{MOM}$				0.026		0.051
t-stat				*1.02*		*2.70*

Panel E. Alphas and Betas of FVIXind (Industry-based)

	Raw	CAPM	FF	Carhart	FF5	FF6
$\boldsymbol{\alpha}$	-1.385	-0.448	-0.443	-0.453	-0.209	-0.236
t-stat	*-4.66*	*-4.73*	*-4.49*	*-4.59*	*-3.08*	*-3.58*
$\boldsymbol{\beta}_{MKT}$		-1.375	-1.395	-1.392	-1.484	-1.477
t-stat		*-38.6*	*-42.6*	*-40.3*	*-74.0*	*-71.1*
$\boldsymbol{\beta}_{SMB}$			0.130	0.130	0.034	0.028
t-stat			*2.81*	*2.94*	*1.29*	*1.20*
$\boldsymbol{\beta}_{HML}$			-0.015	-0.010	0.194	0.229
t-stat			*-0.21*	*-0.14*	*4.26*	*5.11*
$\boldsymbol{\beta}_{CMA}$					-0.321	-0.346
t-stat					*-6.00*	*-5.94*
$\boldsymbol{\beta}_{RMW}$					-0.357	-0.372
t-stat					*-8.67*	*-9.81*
$\boldsymbol{\beta}_{MOM}$				0.013		0.052
t-stat				*0.38*		*2.13*

Panel F. Alphas and Betas of FVIXT (Fully Tradable FVIX)

	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*
$\boldsymbol{\beta}_{CMA}$					-0.082	-0.098
t-stat					*-1.66*	*-2.18*
$\boldsymbol{\beta}_{RMW}$					-0.138	-0.147
t-stat					*-4.60*	*-5.02*
$\boldsymbol{\beta}_{MOM}$				0.029		0.038
t-stat				*1.80*		*2.23*

Panel G. Alphas and Betas of FVIXtr (purged of bad/no Cred)

	Raw	**CAPM**	**FF**	**Carhart**	**FF5**	**FF6**
$\boldsymbol{\alpha}$	-1.347	-0.467	-0.480	-0.494	-0.297	-0.320
t-stat	*-4.49*	*-4.67*	*-4.41*	*-4.52*	*-3.56*	*-3.93*
$\boldsymbol{\beta}_{MKT}$		-1.365	-1.392	-1.387	-1.460	-1.452
t-stat		*-37.6*	*-36.7*	*-35.2*	*-57.9*	*-56.9*
$\boldsymbol{\beta}_{SMB}$			0.236	0.235	0.158	0.152
t-stat			*6.76*	*7.12*	*6.22*	*6.08*
$\boldsymbol{\beta}_{HML}$			0.034	0.041	0.188	0.221
t-stat			*0.62*	*0.76*	*3.36*	*3.83*
$\boldsymbol{\beta}_{CMA}$					-0.222	-0.248
t-stat					*-3.88*	*-4.50*
$\boldsymbol{\beta}_{RMW}$					-0.286	-0.301
t-stat					*-8.17*	*-8.48*
$\boldsymbol{\beta}_{MOM}$				0.018		0.049
t-stat				*0.88*		*2.52*

Table 7A. Distress Risk Puzzle and Alternative FVIX Factors

The table fits the CAPM and the ICAPM with FVIX to the arbitrage portfolios described in the header of Table 8 in the paper and reports alphas and FVIX betas. Other test assets are defined in a similar fashion. All five alternative FVIX definitions described in the header of Table 6A are used, and the ICAPM versions are labeled according to the version of FVIX they use. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

	$\boldsymbol{\alpha}_{CAPM}$	$\boldsymbol{\alpha}_{ICAPM}$	$\boldsymbol{\beta}_{FVIX}$	$\boldsymbol{\alpha}_{ICAPM6}$	$\boldsymbol{\beta}_{FVIX6}$	$\boldsymbol{\alpha}_{ICAPMind}$	$\boldsymbol{\beta}_{FVIXind}$	$\boldsymbol{\alpha}_{ICAPMT}$	$\boldsymbol{\beta}_{FVIXT}$	$\boldsymbol{\alpha}_{ICAPMtr}$	$\boldsymbol{\beta}_{FVIXtr}$
Cred	0.800	0.159	-1.378	0.242	-1.698	0.236	-1.290	0.104	-1.890	0.116	-1.534
t-stat	*3.85*	*0.73*	*-6.99*	*0.98*	*-6.53*	*0.87*	*-7.27*	*0.30*	*-4.42*	*0.44*	*-7.12*
CredDisp	0.733	0.473	-0.514	0.569	-0.468	0.509	-0.488	0.689	-0.825	0.623	-0.239
t-stat	*2.15*	*1.24*	*-1.89*	*1.64*	*-1.21*	*1.44*	*-1.59*	*1.74*	*-1.56*	*1.64*	*-0.68*
CredDispHI	0.867	0.121	-0.927	0.317	-1.572	0.313	-1.205	0.361	-1.862	-0.037	-1.377
t-stat	*2.77*	*0.36*	*-4.79*	*1.08*	*-6.71*	*0.95*	*-3.82*	*0.96*	*-2.79*	*-0.11*	*-4.72*
CredIVol	0.888	0.169	-0.741	0.209	-0.686	0.206	-0.536	0.328	-0.630	0.370	-0.709
t-stat	*2.99*	*0.59*	*-3.31*	*0.71*	*-3.96*	*0.67*	*-2.67*	*0.94*	*-1.42*	*0.78*	*-2.61*
CredIVolHi	1.073	0.094	-1.361	0.210	-1.581	0.221	-1.164	0.092	-1.647	0.141	-1.622
t-stat	*3.80*	*0.34*	*-6.05*	*0.85*	*-7.12*	*0.78*	*-7.06*	*0.30*	*-4.65*	*0.42*	*-6.37*
CredMB	0.457	0.113	-0.740	0.204	-0.728	0.200	-0.557	0.236	-1.046	0.219	-0.511
t-stat	*1.72*	*0.42*	*-3.98*	*0.79*	*-4.58*	*0.74*	*-3.51*	*0.84*	*-3.77*	*0.76*	*-2.68*
CredMBHI	0.860	0.111	-1.609	0.266	-1.708	0.335	-1.137	0.187	-1.790	0.143	-1.787
t-stat	*3.44*	*0.45*	*-5.76*	*1.29*	*-7.36*	*1.36*	*-5.26*	*0.64*	*-3.93*	*0.44*	*-7.51*
O-Score	0.270	0.012	-0.556	0.030	-0.681	0.150	-0.259	-0.064	-0.852	-0.061	-0.681
t-stat	*1.60*	*0.07*	*-4.04*	*0.17*	*-4.29*	*0.89*	*-1.90*	*-0.35*	*-4.86*	*-0.36*	*-7.14*
OMB	0.437	-0.224	-0.880	-0.148	-1.041	-0.013	-0.482	-0.038	-0.604	-0.087	-0.630
t-stat	*1.75*	*-0.64*	*-1.83*	*-0.48*	*-3.52*	*-0.04*	*-1.20*	*-0.09*	*-0.85*	*-0.24*	*-1.43*
OMBHI	0.391	-0.076	-0.945	0.140	-0.990	0.221	-0.554	-0.030	-1.247	0.025	-0.962
t-stat	*2.11*	*-0.32*	*-2.72*	*0.73*	*-7.69*	*1.15*	*-2.88*	*-0.15*	*-3.65*	*0.13*	*-5.68*
EDF	0.198	-0.146	-0.744	-0.050	-0.711	-0.095	-0.653	-0.014	-0.666	-0.107	-0.620
t-stat	*0.78*	*-0.56*	*-4.33*	*-0.19*	*-2.60*	*-0.36*	*-4.10*	*-0.06*	*-2.42*	*-0.41*	*-3.55*

Table 8A. Cross-Sectional Regressions

The table presents the results of firm-level Fama-MacBeth regressions run each month. The dependent variables, as indicated in the header of each column, are firm-level risk-adjusted returns ($\overline{\alpha}$) estimated as in Brennan et al. (1998) (see online Data Appendix). All independent variables but Cred are ranks between 0 and 1. Cred is coded as AAA=1, AA+=2, ... D=22. In each month and for each variable, all firms are ranked in the ascending order and are assigned a rank, with zero (one) for the firm with the lowest (highest) value of the variable. The controls are market-to-book (MB), size, cumulative return between month t-2 and t-12 (MOM), and past month return (REV). Panel A additionally controls for the maximum daily return in the past month (Max), Panel B controls for idiosyncratic volatility (IVol) instead, Panel C controls for analyst disagreement (Disp). Detailed definitions of all variables are in online Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2017. The sample excludes stocks priced below $5 at the portfolio formation date.

Panel A. Distress Risk Puzzle and Maximum Effect

	Raw	$\hat{\boldsymbol{\alpha}}_{CAPM}$	$\hat{\boldsymbol{\alpha}}_{ICAPM}$	$\hat{\boldsymbol{\alpha}}_{FF}$	$\hat{\boldsymbol{\alpha}}_{FF4}$	$\hat{\boldsymbol{\alpha}}_{Carhart}$	$\hat{\boldsymbol{\alpha}}_{5factor}$
Size	-0.644	-0.633	-0.668	-0.485	-0.259	-0.382	-0.291
t-stat	*-1.25*	*-1.31*	*-1.20*	*-1.08*	*-0.51*	*-0.83*	*-0.53*
MB	-0.388	-0.300	-0.113	0.133	0.164	-0.024	-0.194
t-stat	*-1.73*	*-1.25*	*-0.47*	*0.68*	*0.80*	*-0.12*	*-0.93*
Mom	0.839	0.712	0.435	0.501	0.044	0.342	0.239
t-stat	*2.20*	*1.92*	*0.99*	*1.31*	*0.09*	*0.96*	*0.58*
Rev	-0.202	-0.349	-0.391	-0.237	-0.460	-0.265	-0.450
t-stat	*-1.03*	*-1.68*	*-1.54*	*-1.18*	*-1.65*	*-0.91*	*-1.35*
Max	-0.101	-0.482	0.032	-0.457	-0.209	-0.363	-0.028
t-stat	*-0.41*	*-2.17*	*0.14*	*-2.29*	*-0.92*	*-1.79*	*-0.12*
Cred	-3.245	-5.360	0.158	-4.392	-2.235	-3.759	-2.091
t-stat	*-1.52*	*-2.87*	*0.07*	*-2.69*	*-1.25*	*-2.18*	*-1.10*

Panel B. Distress Risk Puzzle and Idiosyncratic Volatility

	Raw	$\hat{\boldsymbol{\alpha}}_{CAPM}$	$\hat{\boldsymbol{\alpha}}_{ICAPM}$	$\hat{\boldsymbol{\alpha}}_{FF}$	$\hat{\boldsymbol{\alpha}}_{FF4}$	$\hat{\boldsymbol{\alpha}}_{Carhart}$	$\hat{\boldsymbol{\alpha}}_{5factor}$
Size	-0.651	-0.786	-0.589	-0.643	-0.349	-0.465	-0.252
t-stat	*-1.28*	*-1.67*	*-1.09*	*-1.50*	*-0.68*	*-1.07*	*-0.47*
MB	-0.425	-0.315	-0.126	0.108	0.118	-0.064	-0.184
t-stat	*-1.92*	*-1.35*	*-0.52*	*0.61*	*0.59*	*-0.33*	*-0.86*
Mom	0.991	0.772	0.771	0.434	0.181	0.196	0.316
t-stat	*2.40*	*1.90*	*1.53*	*1.11*	*0.36*	*0.48*	*0.62*
Rev	-0.390	-0.383	-0.538	-0.557	-0.697	-0.650	-0.741
t-stat	*-1.93*	*-1.73*	*-1.76*	*-2.28*	*-2.06*	*-2.16*	*-2.10*
IVol	-0.531	-0.899	-0.014	-0.991	-0.494	-0.982	-0.373
t-stat	*-1.80*	*-3.18*	*-0.04*	*-3.89*	*-1.55*	*-3.85*	*-1.21*
Cred	-2.322	-5.091	-0.128	-4.460	-2.468	-3.891	-2.407
t-stat	*-1.11*	*-2.84*	*-0.06*	*-2.99*	*-1.53*	*-2.75*	*-1.49*

Panel C. Distress Risk Puzzle and Analyst Disagreement

	Raw	$\hat{\boldsymbol{\alpha}}_{CAPM}$	$\hat{\boldsymbol{\alpha}}_{ICAPM}$	$\hat{\boldsymbol{\alpha}}_{FF}$	$\hat{\boldsymbol{\alpha}}_{FF4}$	$\hat{\boldsymbol{\alpha}}_{Carhart}$	$\hat{\boldsymbol{\alpha}}_{5factor}$
Size	-0.066	-0.129	-0.362	0.199	0.172	0.071	0.126
t-stat	*-0.11*	*-0.21*	*-0.55*	*0.35*	*0.30*	*0.13*	*0.21*
MB	-0.678	-0.575	-0.072	-0.180	0.062	-0.289	-0.173
t-stat	*-2.75*	*-2.37*	*-0.33*	*-0.99*	*0.34*	*-1.46*	*-0.83*
Mom	0.779	0.540	0.449	0.224	-0.120	0.030	-0.011
t-stat	*1.83*	*1.28*	*0.99*	*0.54*	*-0.26*	*0.07*	*-0.02*
Rev	-0.408	-0.361	-0.609	-0.524	-0.686	-0.644	-0.767
t-stat	*-1.84*	*-1.56*	*-2.11*	*-2.08*	*-2.20*	*-2.14*	*-2.34*
Disp	-0.316	-0.475	-0.318	-0.599	-0.506	-0.576	-0.396
t-stat	*-1.43*	*-2.17*	*-1.33*	*-2.87*	*-2.28*	*-2.76*	*-1.77*
Cred	-1.108	-4.583	1.675	-3.709	-1.744	-3.834	-1.713
t-stat	*-0.44*	*-2.17*	*0.75*	*-1.94*	*-0.92*	*-2.12*	*-0.90*

Table 9A. Distress Risk Puzzle and Related Anomalies

The table presents the results of firm-level Fama-MacBeth regressions run each month. The dependent variable is firm-level risk-adjusted returns estimated as in Brennan et al. (1998). In Panel A, the dependent variable is the CAPM alpha, $\alpha_t^{CAPM} = Ret_t - \beta_{t-1;\ t-36} \cdot MKT_t$, where $\beta_{t-1;\ t-36}$ is the firm-level beta estimated in each month t by regressing the firm's monthly excess returns on the market excess returns using data from months t-1 to t-36. In Panel B, the dependent variable is the alpha from the two-factor ICAPM with the market factor and FVIX, computed in a similar fashion. Common control variables are market-to-book (MB), market cap (Size), cumulative return between month t-2 and t-12 (MOM), and return in the past month (REV). All control variables are ranks between 0 and 1. In each month, all firms are ranked in the ascending order on the variable in question and then each firm is assigned its rank, with zero (one) assigned to the firm with the lowest (highest) value of the ranking variable. TopCred is the dummy variable that equals one if the firm falls into the worst credit rating quintile, and zero otherwise. Additional controls are similarly constructed dummies for top quintiles in terms of idiosyncratic volatility (TopIVol), gross profitability (TopGProf), maximum daily return in the past month (TopMax), and analyst disagreement (TopDisp). Detailed definitions of all variables are in online Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2017. The sample excludes stocks priced below $5 at the portfolio formation date.

Panel A. BCS Regressions with Top Quintile Dummies: CAPM Alphas on the LHS

	1	2	3	4	5	6	7	8	9	10	11
Size	-0.058	-0.443	-0.242	-1.081	-0.144	-0.136	0.185	0.033	-0.210	0.062	-0.018
t-stat	*-0.12*	*-1.92*	*-0.52*	*-2.99*	*-0.30*	*-0.47*	*0.35*	*0.05*	*-0.60*	*0.10*	*-0.04*
MB	-0.286	-0.652	-0.264	-0.895	-0.262	-0.809	-0.394	-0.388	-0.499	-0.380	-0.362
t-stat	*-1.35*	*-2.36*	*-1.25*	*-3.13*	*-1.23*	*-3.00*	*-1.57*	*-1.85*	*-1.57*	*-1.77*	*-1.45*
Mom	0.789	0.946	0.740	0.573	0.736	1.037	0.884	0.819	0.600	0.647	0.792
t-stat	*2.08*	*2.96*	*1.97*	*1.61*	*1.99*	*3.68*	*2.32*	*2.09*	*1.79*	*1.68*	*2.12*
Rev	-0.373	-0.239	-0.376	-0.329	-0.409	-0.241	-0.357	-0.410	-0.340	-0.338	-0.398
t-stat	*-1.71*	*-1.41*	*-1.72*	*-1.96*	*-1.88*	*-1.36*	*-1.61*	*-1.82*	*-1.89*	*-1.45*	*-1.80*
TopCred	-0.386		-0.309		-0.320		-0.396	-0.302		-0.256	-0.317
t-stat	*-2.48*		*-2.09*		*-2.12*		*-2.58*	*-2.15*		*-1.81*	*-2.15*
TopIVol		-0.365	-0.289								-0.169
t-stat		*-3.42*	*-2.70*								*-1.68*
TopMax				-0.522	-0.306						-0.213
t-stat				*-4.41*	*-2.51*						*-1.73*
TopGProf						0.183	0.238				0.234
t-stat						*2.01*	*2.32*				*2.31*
TopDisp									-0.304	-0.194	
t-stat									*-2.97*	*-1.55*	

Panel B. BCS Regressions with Top Quintile Dummies: ICAPM Alphas on the LHS

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Size	-0.643	-0.854	-0.711	-1.676	-0.663	-0.862	-0.499	-0.577	-1.045	-0.558	-0.562
t-stat	*-1.31*	*-3.44*	*-1.46*	*-4.54*	*-1.36*	*-2.84*	*-0.91*	*-0.95*	*-2.82*	*-0.92*	*-1.04*
MB	0.040	-0.065	0.046	-0.316	0.067	-0.024	0.044	-0.035	0.206	-0.017	0.064
t-stat	*0.18*	*-0.23*	*0.21*	*-1.06*	*0.30*	*-0.08*	*0.17*	*-0.17*	*0.64*	*-0.08*	*0.25*
Mom	0.677	0.847	0.656	0.379	0.643	0.918	0.773	0.685	0.521	0.519	0.717
t-stat	*1.57*	*2.11*	*1.55*	*0.86*	*1.53*	*2.92*	*1.77*	*1.58*	*1.29*	*1.21*	*1.69*
Rev	-0.574	-0.405	-0.553	-0.405	-0.593	-0.431	-0.555	-0.602	-0.535	-0.566	-0.574
t-stat	*-2.09*	*-1.70*	*-2.02*	*-1.60*	*-2.14*	*-1.80*	*-1.98*	*-2.18*	*-2.12*	*-2.03*	*-2.04*
TopCred	-0.072		-0.057		-0.058		-0.075	0.043		0.096	-0.074
t-stat	*-0.49*		*-0.39*		*-0.40*		*-0.52*	*0.34*		*0.73*	*-0.51*
TopIVol		-0.014	-0.050								-0.022
t-stat		*-0.13*	*-0.42*								*-0.18*
TopMax				-0.213	-0.039						-0.010
t-stat				*-1.83*	*-0.31*						*-0.08*
TopGProf						0.023	0.141				0.141
t-stat						*0.23*	*1.24*				*1.25*
TopDisp									-0.097	-0.117	
t-stat									*-0.93*	*-0.86*	

Table 10A. Unlevered Volatility Measures

The table reports median values of several firm-specific uncertainty measures (named in the headings of the panels) - idiosyncratic volatility (IVol), analyst disagreement (Disp), analyst forecast error (Error), volatility of cash flows (CVCFO) and earnings (CVEarn), as well as market beta (Beta). For each measure, the respective panel reports, across credit rating quintiles, its median (Raw) and medians of two unlevered versions X^U, calculated using the formula usually used for unlevering the market beta

$$X^U = \frac{Raw}{1+(1-T)\cdot\dfrac{D}{E}}$$

where T is the corporate tax rate and $\dfrac{D}{E}$ is debt-to-equity ratio (can be derived from the leverage measure used throughout the paper as $\dfrac{D}{E} = \dfrac{Lev}{1-Lev}$). In the panels, line *T=0.35* sets the tax corporate tax rate to 35%, whereas line *MargT* uses the marginal tax rate T calculated as in Blouin et al. (2010) and provided by Compustat. The formula is applied to all uncertainty measures at the firm level, and then the median is calculated within each credit rating quintile. Detailed definitions of all variables are in online Data Appendix. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017. The sample excludes stocks priced below $5 on the portfolio formation date.

Panel A. Raw and Unlevered IVol

	Best	**Cred2**	**Cred3**	**Cred4**	**Worst**	**W-B**	**t(W-B)**
	A+	*BBB+*	*BBB-*	*BB*	*B+*		
Raw	1.122	1.324	1.477	1.782	2.347	1.225	*30.3*
T=0.35	0.990	1.092	1.137	1.234	1.420	0.430	*22.2*
MargT	0.992	1.095	1.138	1.228	1.392	0.401	*21.0*

Panel B. Raw and Unlevered Beta

	Best	**Cred2**	**Cred3**	**Cred4**	**Worst**	**W-B**	**t(W-B)**
	A+	*BBB+*	*BBB-*	*BB*	*B+*		
Raw	0.887	1.014	1.087	1.225	1.396	0.509	*17.7*
T=0.35	0.778	0.834	0.837	0.839	0.835	0.057	*2.29*
MargT	0.778	0.834	0.836	0.834	0.821	0.042	*1.76*

Panel C. Raw and Unlevered Disp

	Best	Cred2	Cred3	Cred4	Worst	W-B	t(W-B)
Raw	0.021	0.033	0.041	0.058	0.100	0.080	*16.6*
T=0.35	0.018	0.026	0.031	0.038	0.059	0.041	*17.0*
MargT	0.018	0.026	0.031	0.038	0.058	0.040	*15.9*

Panel D. Raw and Unlevered Error

	Best	Cred2	Cred3	Cred4	Worst	W-B	t(W-B)
Raw	0.033	0.064	0.081	0.123	0.221	0.187	*14.5*
T=0.35	0.029	0.053	0.064	0.083	0.133	0.104	*15.9*
MargT	0.029	0.053	0.064	0.083	0.131	0.102	*15.2*

Panel E. Raw and Unlevered CVCFO

	Best	Cred2	Cred3	Cred4	Worst	W-B	t(W-B)
Raw	0.541	0.755	0.922	1.049	1.512	0.971	*14.3*
T=0.35	0.486	0.621	0.724	0.757	0.928	0.442	*13.1*
MargT	0.487	0.624	0.723	0.755	0.918	0.431	*12.5*

Panel F. Raw and Unlevered CVEarn

	Best	Cred2	Cred3	Cred4	Worst	W-B	t(W-B)
Raw	0.386	0.623	0.864	1.239	1.923	1.536	*29.2*
T=0.35	0.342	0.511	0.669	0.857	1.108	0.766	*20.1*
MargT	0.342	0.512	0.666	0.848	1.093	0.750	*20.3*

Table 11A. Uncertainty Measures Orthogonalized to Leverage

The table reports, across credit rating quintiles, median values of several firm-specific uncertainty measures - idiosyncratic volatility (IVol), analyst disagreement (Disp), analyst forecast error (Error), volatility of cash flows (CVCFO) and earnings (CVEarn), as well as market beta - orthogonalized to market leverage (Lev). The orthogonalized uncertainty measures are residuals from monthly cross-sectional regressions of log(1+X), where X is one of the uncertainty measures, on log of (1+Lev) and the square of log of (1+Lev). The credit rating quintiles are formed using NYSE (exchcd=1) breakpoints and rebalanced monthly. Detailed definitions of all variables are in online Data Appendix. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017. The sample excludes stocks priced below $5 on the portfolio formation date.

	Best	**Cred2**	**Cred3**	**Cred4**	**Worst**	**W-B**
	A+	*BBB+*	*BBB-*	*BB*	*B+*	
IVol	-0.038	0.027	0.077	0.138	0.189	0.227
t-stat	*-13.4*	*14.7*	*44.7*	*45.5*	*42.5*	*67.2*
Disp	-0.019	0.042	0.088	0.144	0.181	0.201
t-stat	*-11.1*	*19.7*	*29.8*	*41.1*	*38.8*	*41.9*
Error	-0.011	0.038	0.076	0.128	0.170	0.181
t-stat	*-4.68*	*19.3*	*33.6*	*47.9*	*41.3*	*57.6*
CVCFO	-0.050	0.016	0.062	0.125	0.182	0.232
t-stat	*-10.8*	*6.39*	*34.5*	*43.6*	*60.0*	*64.7*
CVEarn	-0.030	0.029	0.077	0.136	0.183	0.213
t-stat	*-15.5*	*16.0*	*35.1*	*41.9*	*38.6*	*47.0*

Table 12A. The Role of Operating Leverage

Panel A reports, across credit rating quintiles, median values of leverage (Lev), operating leverage (OpLev), ratio of SG&A to book value (SG&A), and ratios of R&D spending to total assets (TA) and to market cap (Size). Panel B reports value-weighted (Panel B1) and equal-weighted (Panel B2) CAPM alphas, as well as alphas and FVIX betas from the two-factor ICAPM with the market factor and FVIX fitted to quintile portfolios sorted on operating leverage (OpLev, abbreviated to OL). FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. The credit rating and operating leverage quintiles are formed using NYSE (exchcd=1) breakpoints and rebalanced monthly. Detailed definitions of all variables are in online Data Appendix. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017. The sample excludes stocks priced below $5 on the portfolio formation date.

Panel A. Operating Leverage and Credit Rating

	Best *A+*	**Cred2** *BBB+*	**Cred3** *BBB-*	**Cred4** *BB*	**Worst** *B+*	**W-B**	**t(W-B)**
Lev	0.138	0.212	0.266	0.356	0.443	0.305	*43.4*
OpLev	1.824	2.050	2.201	2.199	2.371	0.546	*12.4*
SG&A	0.486	0.421	0.398	0.385	0.488	0.002	*0.14*
R&D/TA	0.021	0.018	0.016	0.013	0.012	-0.009	*-6.65*
R&D/Size	0.017	0.018	0.019	0.023	0.020	0.004	*2.48*

Panel B. Operating Leverage and Aggregate Volatility Risk

Panel B1. Value-Weighted Returns

	Low	**OL2**	**OL3**	**OL4**	**High**	**L-H**
$\boldsymbol{\alpha}_{CAPM}$	-0.134	0.067	0.234	0.046	0.108	-0.242
t-stat	*-0.89*	*0.86*	*2.77*	*0.44*	*0.91*	*-1.19*
$\boldsymbol{\alpha}_{ICAPM}$	0.099	-0.083	0.237	0.017	0.057	0.042
t-stat	*0.73*	*-0.83*	*2.14*	*0.14*	*0.42*	*0.19*
$\boldsymbol{\beta}_{FVIX}$	0.486	-0.325	-0.009	-0.077	-0.098	0.584
t-stat	*2.81*	*-2.55*	*-0.06*	*-0.83*	*-1.04*	*2.64*

Panel B2. Equal-Weighted Returns

	Low	**OL2**	**OL3**	**OL4**	**High**	**L-H**
$\boldsymbol{\alpha}_{CAPM}$	-0.011	0.058	0.074	0.065	0.016	0.027
t-stat	*-0.08*	*0.39*	*0.48*	*0.37*	*0.09*	*0.20*
$\boldsymbol{\alpha}_{ICAPM}$	0.233	0.354	0.310	0.304	0.256	0.022
t-stat	*1.47*	*2.01*	*1.83*	*1.60*	*1.26*	*0.15*
$\boldsymbol{\beta}_{FVIX}$	0.524	0.634	0.506	0.520	0.523	-0.001
t-stat	*4.70*	*4.79*	*4.91*	*4.58*	*4.39*	*-0.01*

Table 13A. Idiosyncratic Volatility and the Business Cycle

Panel A (B) presents the slopes from the regressions of the log average idiosyncratic volatility, $log(\overline{IVOL})$ (log average analyst disagreement, $log(\overline{Disp})$). on the business cycle variables. The business cycle variables are the NBER recession dummy, the log of the VIX index, the log market volatility forecast from TARCH(1,1) model, and the log realized market volatility. The numbers in the first row are the number of months by which I lag the business cycle in each column. The slopes indicate the percentage point increase in the average IVol when either the NBER dummy changes from zero to one or any of the other variables increases by 1%. Detailed definitions of all variables are in online Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

Panel A. Average Idiosyncratic Volatility Predicted by Business Cycle Variables

	-12	**-9**	**-6**	**-3**	**0**	**3**	**6**	**9**	**12**
NBER	17.80	22.85	24.90	28.70	30.12	22.92	14.940	1.366	-7.346
t-stat	*2.27*	*2.35*	*2.77*	*3.57*	*3.77*	*2.61*	*1.67*	*0.17*	*-0.87*
VIX	0.098	0.140	0.170	0.223	0.295	0.205	0.134	0.107	0.072
t-stat	*1.59*	*2.28*	*2.64*	*3.31*	*4.29*	*2.94*	*2.06*	*1.76*	*1.17*
TARCH	0.042	0.087	0.151	0.252	0.385	0.328	0.247	0.200	0.138
t-stat	*0.64*	*1.29*	*2.01*	*3.06*	*4.83*	*3.86*	*2.85*	*2.56*	*1.86*
Realized	0.061	0.089	0.121	0.159	0.229	0.133	0.079	0.051	0.016
t-stat	*1.57*	*2.19*	*2.72*	*3.29*	*4.53*	*2.66*	*1.80*	*1.34*	*0.40*

Panel B. Average Analyst Disagreement Predicted by Business Cycle Variables

	-12	**-9**	**-6**	**-3**	**0**	**3**	**6**	**9**	**12**
NBER	20.41	19.28	20.23	22.95	18.37	7.08	-4.573	-8.644	-10.903
t-stat	*2.23*	*2.29*	*2.44*	*2.86*	*2.43*	*1.20*	*-0.61*	*-1.07*	*-1.58*
VIX	0.119	0.184	0.242	0.176	0.137	0.158	0.147	0.087	0.057
t-stat	*1.95*	*3.08*	*3.68*	*2.49*	*1.93*	*2.38*	*2.36*	*1.29*	*0.75*
TARCH	0.102	0.189	0.275	0.252	0.232	0.249	0.221	0.159	0.139
t-stat	*1.36*	*2.56*	*3.41*	*3.06*	*2.81*	*2.95*	*2.87*	*1.99*	*1.49*
Realized	0.078	0.102	0.135	0.096	0.086	0.066	0.056	0.027	0.029
t-stat	*1.94*	*2.27*	*2.44*	*1.85*	*1.76*	*1.53*	*1.40*	*0.63*	*0.60*

Table 14A. Distress Risk Puzzle, Short-Run and Long-Run Volatility

The paper presents alphas (Panel A) and volatility risk betas (Panel B) from the following six models:

$$Model\ 0 \ : \ Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) \tag{4}$$

$$Model\ 1 \ : \ Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t \tag{5}$$

$$Model\ 2 \ : \ Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{LR} \cdot LR_t + \beta_{SR} \cdot SR_t \tag{6}$$

$$Model\ 3 \ : \ Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t + \beta_{LR} \cdot LR_t + \beta_{SR} \cdot SR_t \tag{7}$$

$$Model\ 4 \ : \ Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{SR} \cdot SR_t \tag{8}$$

$$Model\ 5 \ : \ Ret_t - RF_t = \alpha + \beta \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t + \beta_{SR} \cdot SR_t \tag{9}$$

The volatility risk factors are FVIX (the factor-mimicking portfolio tracking changes in VIX), SR (the factor-mimicking portfolio tracking changes in short-run market volatility component), and LR (the factor-mimicking portfolio tracking changes in long-run market volatility component). The short-run and long-run market volatility components are from the C-GARCH model in Adrian and Rosenberg (2008). Detailed descriptions of the factor-mimicking procedure are in online Data Appendix.

The test assets on the left-hand side of the equations above are the arbitrage portfolios labeled the following way: Cred buys/shorts firms in the best/wosrt credit rating quintile; CredDispHI does the same within the top Disp group (top 30% of firms in terms of analyst disagreement). CredDisp compares CredDispHI with similarly defined CredDispLow. Other test assets are defined in a similar fashion.

The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017. The sample used to form the low-minus-high portfolios excludes the stocks with per share price less than $5 on the portfolio formation date.

Panel A. Alphas from Models with Different Volatility Risk Factors

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5
Cred	0.800	0.159	0.554	0.255	0.605	0.227
t-stat	*3.85*	*0.73*	*2.96*	*1.34*	*2.85*	*1.08*
CredDisp	0.733	0.473	0.609	0.528	0.614	0.528
t-stat	*2.15*	*1.24*	*1.84*	*1.46*	*1.86*	*1.46*
CredDispHI	0.867	0.121	0.565	0.229	0.619	0.216
t-stat	*2.77*	*0.36*	*2.01*	*0.79*	*2.13*	*0.72*
CredIVol	0.888	0.169	0.774	0.581	0.778	0.582
t-stat	*2.99*	*0.59*	*2.73*	*2.06*	*2.78*	*2.06*
CredIVolHi	1.073	0.094	0.851	0.513	0.894	0.496
t-stat	*3.80*	*0.34*	*3.11*	*2.14*	*3.29*	*2.01*
CredMB	0.457	0.113	0.353	0.145	0.376	0.134
t-stat	*1.72*	*0.42*	*1.34*	*0.56*	*1.43*	*0.51*
CredMBHI	0.860	0.111	0.575	0.221	0.628	0.193
t-stat	*3.44*	*0.45*	*2.73*	*1.09*	*2.68*	*0.87*
O-Score	0.270	0.012	0.299	0.248	0.298	0.244
t-stat	*1.60*	*0.07*	*2.84*	*1.99*	*2.71*	*1.93*
OMB	0.437	-0.224	0.258	0.241	0.257	0.225
t-stat	*1.75*	*-0.64*	*1.64*	*1.20*	*1.63*	*1.09*
OMBHI	0.391	-0.076	0.514	0.387	0.512	0.376
t-stat	*2.11*	*-0.32*	*3.80*	*2.41*	*3.69*	*2.27*
EDF	0.198	-0.146	0.167	-0.042	0.165	-0.063
t-stat	*0.78*	*-0.56*	*1.05*	*-0.20*	*0.93*	*-0.29*

Panel B. Volatility Risk Betas from Models with Different Volatility Risk Factors

	Model 1	Model 2		Model 3			4	Model 5	
	$\boldsymbol{\beta}_{FVIX}$	$\boldsymbol{\beta}_{SR}$	$\boldsymbol{\beta}_{LR}$	$\boldsymbol{\beta}_{FVIX}$	$\boldsymbol{\beta}_{SR}$	$\boldsymbol{\beta}_{LR}$	$\boldsymbol{\beta}_{SR}$	$\boldsymbol{\beta}_{FVIX}$	$\boldsymbol{\beta}_{SR}$
Cred	-0.726	-0.153	0.008	-0.565	-0.105	0.006	-0.159	-0.601	-0.106
t-stat	*-4.30*	*-3.24*	*2.34*	*-3.89*	*-2.55*	*1.98*	*-3.45*	*-4.42*	*-2.59*
CredDisp	-0.514	-0.160	0.005	-0.336	-0.132	0.004	-0.164	-0.358	-0.133
t-stat	*-1.89*	*-1.85*	*0.80*	*-1.24*	*-1.55*	*0.58*	*-1.91*	*-1.37*	*-1.56*
CredDispHI	-0.927	-0.207	0.008	-0.719	-0.145	0.006	-0.213	-0.754	-0.146
t-stat	*-4.79*	*-3.79*	*1.57*	*-3.54*	*-2.65*	*1.11*	*-4.06*	*-3.92*	*-2.75*
CredIVol	-0.741	-0.188	0.002	-0.494	-0.138	-0.001	-0.192	-0.488	-0.137
t-stat	*-3.31*	*-4.02*	*0.30*	*-1.91*	*-2.49*	*-0.14*	*-4.22*	*-1.96*	*-2.45*
CredIVolHI	-1.361	-0.268	0.018	-0.865	-0.180	0.014	-0.311	-0.992	-0.199
t-stat	*-6.05*	*-5.18*	*3.20*	*-3.68*	*-3.33*	*2.41*	*-6.40*	*-4.62*	*-3.75*
CredMB	-0.740	-0.117	0.011	-0.533	-0.062	0.008	-0.141	-0.605	-0.073
t-stat	*-3.98*	*-2.17*	*1.76*	*-2.38*	*-1.20*	*1.32*	*-2.79*	*-2.97*	*-1.45*
CredMBHI	-1.609	-0.348	0.024	-0.907	-0.255	0.020	-0.405	-1.085	-0.282
t-stat	*-5.76*	*-6.69*	*3.61*	*-4.16*	*-5.22*	*3.13*	*-8.60*	*-5.12*	*-5.56*
O-Score	-0.556	-0.032	0.021	-0.435	-0.010	0.009	-0.017	-0.523	-0.019
t-stat	*-4.04*	*-0.73*	*7.17*	*-2.70*	*-0.16*	*2.66*	*-0.36*	*-3.40*	*-0.33*
OMB	-0.880	-0.201	0.009	-0.226	-0.275	0.011	-0.196	-0.323	-0.291
t-stat	*-1.83*	*-2.12*	*1.48*	*-0.85*	*-2.39*	*1.61*	*-1.95*	*-1.35*	*-2.53*
OMBHI	-0.945	-0.186	0.019	-0.422	-0.209	0.011	-0.173	-0.516	-0.224
t-stat	*-2.72*	*-2.77*	*5.46*	*-1.46*	*-2.09*	*2.80*	*-2.28*	*-1.99*	*-2.26*
EDF	-0.744	-0.005	0.028	-0.567	-0.028	0.011	0.017	-0.673	-0.039
t-stat	*-4.33*	*-0.10*	*4.93*	*-3.18*	*-0.37*	*1.54*	*0.25*	*-3.86*	*-0.52*

Table 15A. Conditional CAPM and Aggregate Volatility Risk

Panel A reports alphas from several versions of the Conditional CAPM across credit rating quintiles. CCAPM4 uses default premium (Baa-Aaa yield spread), dividend yield of the market portfolio, term spread (yield to 10-year Treasuries minus yield to 1-year Treasuries), and 1-month Treasury bill yield as conditioning variables:

$$\begin{aligned} Ret_t - RF_t \;=\; & \alpha + \gamma_0 \cdot (MKT_t - RF_t) + \gamma_1 \cdot DEF_{t-1} \cdot (MKT_t - RF_t) \\ & + \gamma_2 \cdot DIV_{t-1} \cdot (MKT_t - RF_t) + \gamma_3 \cdot TB_{t-1} \cdot (MKT_t - RF_t) \\ & + \gamma_4 \cdot TERM_{t-1} \cdot (MKT_t - RF_t) \end{aligned} \tag{10}$$

CCAPM3 uses VIX, market return in the previous month, and lagged quintile portfolio beta as conditioning variables.

$$\begin{aligned} Ret_t - RF_t \;=\; & \alpha + \gamma_0 \cdot (MKT_t - RF_t) + \gamma_1 \cdot VIX_{t-1} \cdot (MKT_t - RF_t) \\ & + \gamma_2 \cdot MKT_{t-1} \cdot (MKT_t - RF_t) + \gamma_3 \cdot \beta^{Q}_{t-3,\ t-1} \cdot (MKT_t - RF_t) \end{aligned} \tag{11}$$

CCAPM7 uses all seven conditioning variables from CCAPM3 and CCAPM4.

$$\begin{aligned} Ret_t - RF_t \;=\; & \alpha + \gamma_0 \cdot (MKT_t - RF_t) + \gamma_1 \cdot DEF_{t-1} \cdot (MKT_t - RF_t) \\ & + \gamma_2 \cdot DIV_{t-1} \cdot (MKT_t - RF_t) + \gamma_3 \cdot TB_{t-1} \cdot (MKT_t - RF_t) \\ & + \gamma_4 \cdot TERM_{t-1} \cdot (MKT_t - RF_t) + \gamma_5 \cdot VIX_{t-1} \cdot (MKT_t - RF_t) \\ & + \gamma_6 \cdot MKT_{t-1} \cdot (MKT_t - RF_t) + \gamma_7 \cdot \beta^{Q}_{t-3,\ t-1} \cdot (MKT_t - RF_t) \end{aligned} \tag{12}$$

Panels B and C add the FVIX factor to all models in Panel A and report alphas and FVIX betas, respectively.

For example, I-CCAPM4 is the model with the market factor and FVIX, in which the market beta (but not the FVIX beta) is conditional on default premium, dividend yield, term premium, and Treasury bill yield.

$$\begin{aligned} Ret_t - RF_t \;=\; & \alpha + \gamma_0 \cdot (MKT_t - RF_t) + \gamma_1 \cdot DEF_{t-1} \cdot (MKT_t - RF_t) \\ & + \gamma_2 \cdot DIV_{t-1} \cdot (MKT_t - RF_t) + \gamma_3 \cdot TB_{t-1} \cdot (MKT_t - RF_t) \\ & + \gamma_4 \cdot TERM_{t-1} \cdot (MKT_t - RF_t) + \beta^{I-CCAPM4}_{FVIX} \cdot FVIX_t \end{aligned} \tag{13}$$

FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Panel A. Alphas from CAPM and Conditional CAPM

	Best *A+*	Cred2 *BBB+*	Cred3 *BBB-*	Cred4 *BB*	Worst *B+*	W-B
$\boldsymbol{\alpha}_{CAPM}$	0.142	-0.138	-0.007	-0.496	-0.690	0.832
t-stat	*2.12*	*-1.36*	*-0.05*	*-2.98*	*-2.80*	*2.86*
$\boldsymbol{\alpha}_{CCAPM4}$	0.100	-0.086	-0.081	-0.451	-0.432	0.532
t-stat	*1.48*	*-0.96*	*-0.70*	*-2.84*	*-1.77*	*1.90*
$\boldsymbol{\alpha}_{CCAPM3}$	0.149	-0.065	-0.019	-0.429	-0.573	0.731
t-stat	*2.37*	*-0.70*	*-0.16*	*-2.52*	*-2.39*	*2.64*
$\boldsymbol{\alpha}_{CCAPM7}$	0.106	-0.063	-0.083	-0.462	-0.484	0.591
t-stat	*1.53*	*-0.69*	*-0.71*	*-2.84*	*-1.92*	*2.03*

Panel B. Alphas from CAPM and CCAPM Augmented with FVIX

	Best *A+*	Cred2 *BBB+*	Cred3 *BBB-*	Cred4 *BB*	Worst *B+*	W-B
$\boldsymbol{\alpha}_{ICAPM}$	-0.070	-0.038	0.081	-0.300	-0.094	0.024
t-stat	*-0.79*	*-0.42*	*0.57*	*-1.59*	*-0.40*	*0.08*
$\boldsymbol{\alpha}_{I-CCAPM4}$	-0.076	-0.019	0.008	-0.307	0.019	-0.095
t-stat	*-0.87*	*-0.23*	*0.06*	*-1.63*	*0.08*	*-0.33*
$\boldsymbol{\alpha}_{I-CCAPM3}$	-0.035	0.007	0.064	-0.287	-0.132	0.111
t-stat	*-0.40*	*0.08*	*0.45*	*-1.53*	*-0.55*	*0.38*
$\boldsymbol{\alpha}_{I-CCAPM7}$	-0.061	-0.004	0.004	-0.321	-0.068	0.013
t-stat	*-0.68*	*-0.05*	*0.03*	*-1.72*	*-0.27*	*0.04*

Panel C. FVIX Betas from CAPM and CCAPM Augmented with FVIX

	Best *A+*	Cred2 *BBB+*	Cred3 *BBB-*	Cred4 *BB*	Worst *B+*	W-B
$\boldsymbol{\beta}_{FVIX}^{ICAPM}$	-0.456	0.215	0.189	0.421	1.280	-1.736
t-stat	*-4.41*	*2.90*	*1.04*	*2.01*	*6.50*	*-6.87*
$\boldsymbol{\beta}_{FVIX}^{I-CCAPM4}$	-0.427	0.163	0.217	0.351	1.095	-1.522
t-stat	*-4.17*	*2.32*	*1.33*	*1.82*	*6.43*	*-6.59*
$\boldsymbol{\beta}_{FVIX}^{I-CCAPM3}$	-0.422	0.169	0.196	0.331	1.036	-1.453
t-stat	*-4.09*	*2.54*	*1.26*	*1.64*	*5.90*	*-6.17*
$\boldsymbol{\beta}_{FVIX}^{I-CCAPM7}$	-0.409	0.150	0.219	0.357	1.049	-1.447
t-stat	*-4.05*	*2.39*	*1.40*	*1.94*	*6.05*	*-6.28*

Table 16A. Conditional CAPM Betas

The table reports betas from the Conditional CAPM that uses default premium (DEF, defined as Baa-Aaa yield spread), dividend yield of the market portfolio (DIV), term spread TERM), and 1-month Treasury bill yield (TB) as conditioning variables:

$$\begin{aligned} Ret_t - RF_t &= \alpha + \gamma_0 \cdot (MKT_t - RF_t) + \gamma_1 \cdot DEF_{t-1} \cdot (MKT_t - RF_t) \\ &\quad + \gamma_2 \cdot DIV_{t-1} \cdot (MKT_t - RF_t) + \gamma_3 \cdot TB_{t-1} \cdot (MKT_t - RF_t) \\ &\quad + \gamma_4 \cdot TERM_{t-1} \cdot (MKT_t - RF_t) \end{aligned} \tag{14}$$

The test assets on the left-hand side of the equation above are the arbitrage portfolios labeled the following way: Cred buys/shorts firms in the best/wosrt credit rating quintile; CredDispHi does the same within the top Disp group (top 30% of firms in terms of analyst disagreement). CredDisp deducts from returns to CredDispHi returns to similarly defined CredDispLow. Other test assets are defined in a similar fashion using IVol/MB instead of Disp.

Recessions/expansions are defined as periods when expected market return predicted by the same four variables (DEF, DIV, TERM, TB) is above/below in-sample median. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

	Value-Weighted			**Equal-Weighted**		
	$\boldsymbol{\beta_{Rec}}$	$\boldsymbol{\beta_{Exp}}$	$\boldsymbol{\beta_{Rec} - \beta_{Exp}}$	$\boldsymbol{\beta_{Rec}}$	$\boldsymbol{\beta_{Exp}}$	$\boldsymbol{\beta_{Rec} - \beta_{Exp}}$
Cred	-0.247	-1.041	0.794	-0.375	-0.602	0.226
t-stat	*-5.43*	*-21.4*	*11.2*	*-8.48*	*-15.4*	*3.71*
CredDisp	0.077	-0.266	0.343	0.007	-0.242	0.249
t-stat	*2.50*	*-5.11*	*5.44*	*0.32*	*-9.54*	*6.95*
CredDispHi	-0.133	-0.901	0.768	-0.387	-0.651	0.264
t-stat	*-2.8*	*-14.8*	*9.39*	*-11.6*	*-20.2*	*5.48*
CredIVol	-0.050	-0.726	0.677	-0.157	-0.417	0.260
t-stat	*-1.13*	*-17.4*	*10.5*	*-5.97*	*-16.1*	*6.61*
CredIVolHi	-0.215	-0.874	0.659	-0.311	-0.540	0.229
t-stat	*-4.60*	*-17.6*	*9.18*	*-7.40*	*-15.8*	*4.06*
CredMB	0.153	-0.474	0.627	-0.393	-0.484	0.090
t-stat	*4.80*	*-9.60*	*9.93*	*-19.1*	*-11.5*	*1.86*
CredMBHi	-0.120	-1.163	1.042	-0.451	-0.745	0.294
t-stat	*-1.89*	*-18.7*	*11.0*	*-11.5*	*-20.8*	*5.35*

Table 17A. Conditional ICAPM: FVIX Betas and Alternative Definitions of Recession

The table estimates the Conditional ICAPM and reports average conditional FVIX betas in recessions, in expansions, and the difference between the two averages. The Conditional ICAPM uses default premium (DEF, defined as Baa-Aaa yield spread), dividend yield of the market portfolio (DIV), term spread (TERM, defined as yield to 10-year Treasuries minus yield to 1-year Treasuries), and 1-month Treasury bill yield (TB) as conditioning variables:

$$\begin{aligned} Ret_t - RF_t &= \alpha + \beta \cdot (MKT_t - RF_t) + \gamma_0 \cdot FVIX_t + \gamma_1 \cdot DEF_{t-1} \cdot FVIX_t \\ &+ \gamma_2 \cdot DIV_{t-1} \cdot FVIX_t + \gamma_3 \cdot TB_{t-1} \cdot FVIX_t + \gamma_4 \cdot TERM_{t-1} \cdot FVIX_t \end{aligned} \tag{15}$$

The test assets on the left-hand side of the equation above are the arbitrage portfolios labeled the following way: Cred buys/shorts firms in the best/worst credit rating quintile; CredDispHi does the same within the top Disp group (top 30% of firms in terms of analyst disagreement). CredDisp deducts from returns to CredDispHi returns to similarly defined CredDispLow. Other test assets are defined in a similar fashion using IVol/MB instead of Disp.

Panels A1-A3 differ in their definitions of recessions. Panel A1 defines a recession as a period when expected market risk premium, i.e., the fitted part from

$$MKT_t - RF_t = c_0 + c_1 \cdot DEF_{t-1} + c_1 \cdot DIV_{t-1} + c_3 \cdot TB_{t-1} + c_4 \cdot TERM_{t-1} \tag{16}$$

exceeds its in-sample average. Panel A2 defines a recession as a period when expected FVIX, the fitted part from a similar regression,

$$FVIX_t = c_0 + c_1 \cdot DEF_{t-1} + c_1 \cdot DIV_{t-1} + c_3 \cdot TB_{t-1} + c_4 \cdot TERM_{t-1} \tag{17}$$

exceeds its in-sample average. Panel A3 defines a recession as a period when the VIX index is above its average in-sample value.

The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Panel A. FVIX Betas in Expansions and Recessions

A1. Recession: E(MKT) > mean

	β_{Rec}	β_{Exp}	$\beta_R - \beta_E$
Cred	-1.861	-1.528	-0.333
t-stat	*-99.3*	*-57.6*	*-9.38*
CredDisp	-0.302	-0.129	-0.173
t-stat	*-20.5*	*-4.09*	*-4.66*
CredDispHI	-1.606	-1.345	-0.261
t-stat	*-87.6*	*-42.5*	*-6.68*
CredIVol	-0.702	-0.535	-0.167
t-stat	*-39.4*	*-19.3*	*-4.78*
CredIVolHi	-1.101	-1.012	-0.089
t-stat	*-47.6*	*-33.3*	*-2.22*
CredMB	-0.842	-0.928	0.086
t-stat	*-34.4*	*-17.8*	*1.42*
CredMBHI	-1.763	-1.519	-0.244
t-stat	*-99.9*	*-68.7*	*-8.11*

A2. Recession: E(FVIX) < mean

	β_{Rec}	β_{Exp}	$\beta_R - \beta_E$
Cred	-1.884	-1.586	-0.298
t-stat	*-91.3*	*-61.6*	*-8.40*
CredDisp	-0.308	-0.165	-0.142
t-stat	*-18.0*	*-6.69*	*-4.86*
CredDispHI	-1.603	-1.409	-0.194
t-stat	*-73.1*	*-48.9*	*-5.33*
CredIVol	-0.704	-0.572	-0.133
t-stat	*-34.5*	*-24.7*	*-4.32*
CredIVolHi	-1.091	-1.042	-0.049
t-stat	*-41.7*	*-41.9*	*-1.38*
CredMB	-0.875	-0.880	0.005
t-stat	*-31.8*	*-22.6*	*0.12*
CredMBHI	-1.772	-1.568	-0.204
t-stat	*-88.2*	*-70.4*	*-6.53*

A3. Recession: VIX > mean

	$\boldsymbol{\beta_{Rec}}$	$\boldsymbol{\beta_{Exp}}$	$\boldsymbol{\beta_R - \beta_E}$
Cred	-1.817	-1.597	-0.220
t-stat	*-83.6*	*-46.7*	*-5.41*
CredDisp	-0.300	-0.137	-0.164
t-stat	*-21.5*	*-4.54*	*-4.75*
CredDispHI	-1.586	-1.380	-0.206
t-stat	*-89.5*	*-40.2*	*-5.28*
CredIVol	-0.691	-0.553	-0.138
t-stat	*-42.5*	*-19.6*	*-4.27*
CredIVolHi	-1.102	-1.014	-0.088
t-stat	*-56.0*	*-32.9*	*-2.48*
CredMB	-0.814	-0.964	0.150
t-stat	*-40.8*	*-19.3*	*2.70*
CredMBHI	-1.726	-1.575	-0.151
t-stat	*-96.2*	*-54.1*	*-4.53*

Panel B. Alphas

	$\boldsymbol{\alpha}_{CAPM}$	$\boldsymbol{\alpha}_{ICAPM}$	$\boldsymbol{\alpha}_{C-ICAPM}$
Cred	0.832	0.024	-0.150
t-stat	*2.86*	*0.08*	*-0.51*
CredDisp	0.314	0.382	0.283
t-stat	*0.74*	*0.78*	*0.56*
CredDispHI	0.606	-0.006	-0.127
t-stat	*1.71*	*-0.01*	*-0.27*
CredIVol	0.698	0.513	0.440
t-stat	*1.50*	*1.20*	*1.02*
CredIVolHi	0.898	0.423	0.414
t-stat	*2.77*	*1.10*	*1.02*
CredMB	1.330	0.367	0.386
t-stat	*2.44*	*0.88*	*0.82*
CredMBHI	0.976	0.008	-0.098
t-stat	*2.65*	*0.03*	*-0.34*

Table 18A. Credit Rating Sorts: CRSP Breakpoints and No Price Screen

The table reports value-weighted (Panel A) and equal-weighted (Panel B) alphas from the CAPM, the Fama-French model (FF3), and the Carhart model, as well as alphas and FVIX betas from the two-factor ICAPM with the market factor and FVIX, the four-factor model with the three Fama-French factors and FVIX (FF3+V), and the five-factor model (the Carhart model augmented with FVIX, "Carhart+V"). The models are fitted to the quintile portfolios sorted on credit rating from month t-2. The quintiles are formed using CRSP breakpoints and are rebalanced monthly. The top (AveCred) line of each panel reports average credit rating of the quintile. FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2017.

Panel A. Value-Weighted Returns

A1. CAPM as Benchmark Model

	Best	**Cred2**	**Cred3**	**Cred4**	**Worst**	**B-W**
$\boldsymbol{\alpha}_{CAPM}$	0.107	0.068	-0.288	-0.658	-0.821	0.928
t-stat	*1.69*	*0.77*	*-2.11*	*-2.83*	*-2.22*	*2.29*
$\boldsymbol{\alpha}_{ICAPM}$	-0.080	0.113	-0.080	-0.092	-0.058	-0.022
t-stat	*-0.98*	*1.25*	*-0.52*	*-0.43*	*-0.15*	*-0.05*
$\boldsymbol{\beta}_{FVIX}$	-0.401	0.098	0.447	1.217	1.639	-2.040
t-stat	*-4.71*	*1.04*	*2.90*	*5.67*	*4.10*	*-4.62*

Panel B. Equal-Weighted Returns

B1. CAPM as Benchmark Model

	Best	**Cred2**	**Cred3**	**Cred4**	**Worst**	**B-W**
$\boldsymbol{\alpha}_{CAPM}$	0.232	0.231	-0.041	-0.274	-0.608	0.840
t-stat	*2.27*	*1.52*	*-0.21*	*-1.16*	*-1.70*	*2.31*
$\boldsymbol{\alpha}_{ICAPM}$	0.024	0.157	0.098	0.084	0.081	-0.057
t-stat	*0.24*	*0.99*	*0.48*	*0.32*	*0.21*	*-0.14*
$\boldsymbol{\beta}_{FVIX}$	-0.448	-0.159	0.297	0.769	1.481	-1.928
t-stat	*-2.64*	*-0.81*	*1.55*	*3.81*	*5.05*	*-4.79*

A2. Fama-French Model as Benchmark Model

	Best	Cred2	Cred3	Cred4	Worst	B-W
$\boldsymbol{\alpha}_{FF}$	0.116	0.030	-0.302	-0.610	-0.824	0.941
t-stat	*2.23*	*0.36*	*-2.15*	*-2.92*	*-2.52*	*2.70*
$\boldsymbol{\alpha}_{FF+V}$	0.016	0.057	-0.178	-0.289	-0.382	0.398
t-stat	*0.28*	*0.68*	*-1.16*	*-1.44*	*-1.13*	*1.10*
$\boldsymbol{\beta}_{FVIX}$	-0.225	0.062	0.280	0.723	0.996	-1.221
t-stat	*-4.06*	*0.79*	*2.11*	*2.83*	*2.48*	*-2.84*

B2. Fama-French Model as Benchmark Model

	Best	Cred2	Cred3	Cred4	Worst	B-W
$\boldsymbol{\alpha}_{FF}$	0.159	0.102	-0.185	-0.422	-0.754	0.913
t-stat	*1.91*	*0.91*	*-1.42*	*-2.74*	*-2.88*	*3.35*
$\boldsymbol{\alpha}_{FF+V}$	-0.009	-0.020	-0.203	-0.326	-0.483	0.474
t-stat	*-0.11*	*-0.18*	*-1.44*	*-1.72*	*-1.80*	*1.77*
$\boldsymbol{\beta}_{FVIX}$	-0.377	-0.276	-0.042	0.215	0.610	-0.987
t-stat	*-3.75*	*-2.61*	*-0.30*	*1.24*	*2.37*	*-3.15*

A3. Carhart Model as Benchmark Model

	Best	Cred2	Cred3	Cred4	Worst	B-W
$\boldsymbol{\alpha}_{Carhart}$	0.130	0.090	-0.117	-0.266	-0.258	0.388
t-stat	*2.47*	*1.10*	*-0.93*	*-1.28*	*-0.69*	*0.98*
$\boldsymbol{\alpha}_{Carhart+V}$	0.030	0.121	0.018	0.075	0.217	-0.187
t-stat	*0.52*	*1.47*	*0.14*	*0.44*	*0.63*	*-0.50*
$\boldsymbol{\beta}_{FVIX}$	-0.224	0.069	0.300	0.760	1.057	-1.281
t-stat	*-4.10*	*0.87*	*2.85*	*3.75*	*2.82*	*-3.13*

B3. Carhart Model as Benchmark Model

	Best	Cred2	Cred3	Cred4	Worst	B-W
$\boldsymbol{\alpha}_{Carhart}$	0.207	0.210	-0.004	-0.120	-0.252	0.459
t-stat	*2.78*	*2.07*	*-0.03*	*-0.91*	*-0.98*	*1.67*
$\boldsymbol{\alpha}_{Carhart+V}$	0.063	0.072	0.045	-0.050	-0.044	0.107
t-stat	*0.96*	*0.83*	*0.41*	*-0.40*	*-0.24*	*0.54*
$\boldsymbol{\beta}_{FVIX}$	-0.356	-0.233	-0.177	0.016	0.472	-0.828
t-stat	*-3.54*	*-2.74*	*-1.32*	*0.11*	*3.54*	*-4.22*