Robustness Checks for
Profitability Anomaly and Aggregate Volatility Risk

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Abstract

The document collects supplementary tests for the paper "Profitability Anomaly and Aggregate Volatility Risk".

Section 1 looks at credit rating downgrades and finds that during recessions low profitability firms are more likely to be upgraded than high profitability firms, but equally likely to be downgraded. Section 1 also finds that there is no evidence that the profitability anomaly is concentrated around credit rating downgrades, in contrast to several other important anomalies covered in Avramov et al. (2013).

Section 2 performs a spanning test for the lottery factor (FMax) of Bali et al. (2019) and the skewness factor (FSkew) of Bali et al. (2017) and finds that both FVIX and RMW can explain the alphas of FMax and FSkew, but neither FMax nor FSkew can explain the alphas of either FVIX or RMW.

Section 3 looks at alternative definitions of FVIX and finds that results in the paper are robust to excluding the October 19, 1987 outlier and to making FVIX fully tradable. Section 3 also looks at short-run (SR) and long-run (LR) volatility factors constructed using volatility forecast from Component GARCH (C-GARCH) model fitted to the market index. Section 3 finds that FVIX and SR significantly overlap and it is SR rather than LR that helps explain roughly one-half of the profitability anomaly.

Section 4 looks at performance of the Conditional CAPM (C-CAPM) and finds that market beta of the high-minus-low profitability portfolio is strongly countercyclical, indicating risk. C-CAPM can explain roughly one-third of the profitability anomaly, and FVIX largely subsumes the effect of conditioning variables on the alpha of the high-minus-low profitability portfolio.

1 Profitability and Downgrades

1.1 Credit Rating Upgrades and Downgrades throughout the Business Cycle

The main result of the paper is that the high-minus-low profitability strategy (e.g., the RMW factor of Fama and French, 2015) performs worse than expected in bad times. The main piece of evidence is the negative FVIX beta of this strategy: the negative FVIX beta in the two-factor ICAPM with the market factor and FVIX implies that the market-neutral high-minus-low profitability strategy loses when VIX goes up.

It is interesting to verify whether high/low profitability firms also do badly/well during recessions along other, non-price-related measures. On the one hand, the argument in the paper is about convexity in equity value created by risky debt: when volatility increases, very distressed/unprofitable firms become more likely to witness a large positive shock that will save them. They are also more likely to witness a large negative shock, but this shock will partially become debtholders' losses because of limited liability. Hence, in recessions unprofitable firms do not have to perform better than profitable firms in terms of, e.g., earnings growth: even if the bigger earnings shocks caused by higher volatility hit them symmetrically on the negative and positive side, the positive shocks have more impact on equity value because of convexity/limited liability. On the other hand, if for whatever reason in recession positive shocks to unprofitable firms are bigger than negative ones, that fact will further support my claim than unprofitable firms perform better in recession.

Table 1A reports percentage point increases in likelihood of credit rating upgrades and downgrades across profitability quintiles. In Panel A (B), each firm is assigned 1 in the month when an upgrade (downgrade) happened and 0 in all other months. These ones and zeros are then averaged in each profitability quintile, resulting in five time-series of upgrade (downgrade) frequency. Then upgrade (downgrade) series are regressed on a constant and a recession dummy, and slopes are recorded in Panel A (B).

Each row in Table 1A is named after the profitability measure the quintile sorts were performed on: two of them (ROE and gross profitability) are the main measures in the paper (see Table 3) and two more are alternative measures from Ball et al. (2015) and Ball et al. (2015) (see Table 7 in the paper).

I use two definitions of the recession dummy: the first one is based on NBER recessions dates from https://www.nber.org/cycles/cyclesmain.html and takes value of 1 between NBER-defined peak and trough and 0 otherwise. The second recession dummy is based on expected market risk premium and is commonly used in the asset pricing and in particular Conditional CAPM literature (see, e.g., Petkova and Zhang, 2005). I first regress market excess return on four standard predictors of market risk premium: dividend yield, default premium, one-month Treasury bill rate, and term premium. Then I take the fitted value from the regression (expected market risk premium) and assign the value of 1 to months when expected market risk premium is above its in-sample median and 0 to months when it is below.

Theoretically, expected market risk premium is proportional to marginal utility of consumption: when consumption is scarce, investors require a higher rate of return. Thus, expected market risk premium is a better indication of bad times than the NBER recession dummy: consumption often remains high around peak dates, even as a recession begins, but can stay low for a long time after the economy is past the trough date, if the economic recovery is slow and subdued.

The advantage of using the recession dummy based on expected market risk premium over the NBER recession dummy is illustrated by Panel A: Panel A1 on the left uses the former and arrives at puzzling result that for all firms credit rating upgrades are more frequent in recessions than in expansions, while Panel A2 on the right uses the former dummy and finds that frequency of upgrades is significantly lower in recessions in the top two profitability quintile, insignificantly lower in the next two quintiles, and insignificantly positive in the bottom profitability quintile. This pattern confirms that unprofitable firms suffer a smaller, if any, reduction in credit rating upgrades during recessions compared to profitable firms. The rightmost column of Panel A2 tests for significance in the difference in reduction of credit rating upgrade frequencies between top and bottom profitability quintiles and find the difference that favors unprofitable firms significant for two profitability measures and marginally significant at the 10% level for the other two.

The rightmost column of Panel A1 (based on the NBER recession dummy) supports this conclusion with the difference in favor of unprofitable firms being significant for three profitability measures out of four and having the required sign in all four cases. The difference is also economically meaningful: in untabulated results, I look at average upgrade frequency across profitability quintiles and record that in any given month a firm in the bottom profitability quintile has 1.54% to be upgraded by credit rating agencies vs. 1.17% probability for an average firm in the top profitability quintile. Panel A1 then implies that in bad times these probabilities increase by roughly 90% and 50%, respectively, and the difference between them nearly triples.

Panel B looks at extra probability of downgrade in bad times, and Panel B2 that defines bad times based on expected market risk premium shows that all firms exhibit an increase in frequency of downgrades, but the increase is never statistically significant. This is consistent with the evidence in Avramov et al. (2013) who find that credit rating downgrades are largely firm-specific events and the impact of business cycle on them is limited, because idiosyncratic factors are much more important.

Similarly, Panel B2 finds that the difference between the increase in frequency of downgrades between top and bottom profitability quintiles is insignificant, but this latter lack of significance is not a power issue: two profitability measures suggest that in bad times low profitability firms witness a larger increase in frequency of downgrades than high profitability, while two other measures suggest the opposite.

Panel B1, with the NBER recession dummy, again arrives at puzzling evidence that frequency of downgrades is smaller in bad times, but the difference in the change in downgrade frequency between top and bottom profitability quintiles is similar to the one reported in Panel B2 and is also never significant.

To sum up, Table 1A suggests that during bad times profitable firms witness a decrease in frequency of credit rating upgrades and no discernable change in frequency of downgrades. Unprofitable firms, on the other hand, do not see significant changes in either upgrades or downgrades throughout the business cycle. So, in terms of credit rating changes, unprofitable firms do better than profitable firms.

1.2 The Role of Downgrade Events in Generating the Profitability Anomaly

Avramov et al. (2013) find that several important anomalies such as momentum or the idiosyncratic volatility effect of Ang et al. (2006) are concentrated around credit rating downgrades: if one removes from the sample firms that were downgraded six months before or six months after portfolio formation, trading strategies based on these anomalies cease to work. While removing downgrades after portfolio formation introduces look-ahead bias, the lack of alpha for the trading strategies after those downgrades are removed suggests that the strategies do not work for at least 90% of firms that form the trading strategies and all profits come from catching a rare event (downgrade) assuming that shorting right before and especially after downgrades is feasible.

Avramov et al. (2013) did not consider the impact of excluding downgrades on the profitability anomaly, so Table 2A presents the results of doing so and discovers that omitting downgrades six months before and after portfolio formation does not materially impact estimates of the profitability anomaly. For example, Panel B of Table 2A pegs the anomaly in gross profitability sorts at 54.5 bp per month, t-statistic 2.72. Panel A2 of Table 3 in the paper performs same gross profitability sorts without omitting downgrades and estimates the profitability anomaly at 46.9 bp per month, t-statistic 2.48. The only exception are operating profitability sorts of Ball et al. (2015), in which excluding downgrades cuts the top-minus-bottom quintile spread in CAPM alphas by a factor of two.

The lack of impact of omitting downgrades on the profitability anomaly is consistent with two pre-existing pieces of evidence. First, Avramov et al. (2013) find that the value effect is similarly unaffected by removal of downgrades. Second, Fama and French (2015) find that HML, the value factor, is redundant in the presence of RWM, the profitability factor.

It is also interesting that removing downgrades also has no effect on FVIX betas and the ability of FVIX to explain the profitability anomaly. Across four panels in Table 2A that look at four different profitability measures, the high-minus-low profitability spread in FVIX betas has t-statistic of at least -2.74, and FVIX explains at least 60% (and in some cases, up to 100%) of the profitability anomaly, leaving the rest insignificant.

2 Skewness and Lottery Factors

2.1 Defining the Factors

Conrad et al. (2014) show that distressed firms tend to have lottery-like, very positively skewed returns: distressed firms have low, beaten-down stock price, and that creates a large upside potential if they turn things around. My paper shows that unprofitable firms are distressed; consistent with that and consistent with Conrad et al. (2014), a recent paper by Bali et al. (2019) shows that a factor based on expected skewness can explain profitability anomaly and several other anomalies related to convexity in firm value (e.g., the idiosyncratic volatility effect of Ang et al., 2006).

Expected skewness is the fitted value from cross-sectional regression of idiosyncratic skewness on a long list of explanatory variables, which includes measures of distress, profitability, volatility, and growth options, as well as industry dummies. Idiosyncratic skewness is defined in Bali et al. (2019) as skewness of residuals from firm-level regressions of returns on the market factor and its square. After expected skewness is calculated for all firms, the skewness factor (henceforth FSkew) is constructed similar to Fama-French factors, as a long-short portfolio that buys/shorts firms in the bottom/top 30% in terms of skewness.

The link between profitability and FSkew in Bali et al. (2019) is not quite stable: first, Panel B of their Table 4 shows that the ability of FSkew to explain the profitability anomaly is not robust to changing the list of skewness predictors. Second, Table 5 in Bali et al. (2019) reports alphas from the Fama and French (2015) five-factor model across expected skewness deciles and finds that only the alpha of the bottom (negative) skewness decile remains significant. This is the decile opposite to the one populated by lottery-like distressed/unprofitable firms. If one interprets those two results in the spirit of Barillas and Shanken (2017) spanning test, it seems that the profitability factor (RMW) spans high skewness firms (it explains their alphas), but not necessarily the other way around.

In addition to FSkew from Bali et al. (2019), I construct another skewness factor (FSkewO) based on the original expected skewness measure from Boyer et al. (2010). Also, since the argument is that distressed/unprofitable firms are lottery-like, I use another lottery-demand factor (FMax) from Bali et al. (2017). FMax is based on observed average of the highest five daily returns (dubbed Max) in the past month and constructed the same way as FSkew: by going long/short in the bottom/top 30% of firms in terms of Max. The advantage of using FMax is that Max is directly observed, while expected skewness has to be estimated and thus suffers from estimation error.

The rest of this section performs the spanning test recommended by Barillas and Shanken (2017) by first using RMW and FVIX to explain FSkew and FMax, and then using FSkew and FMax to explain FVIX and then RMW.

2.2 Explaining Skewness and Lottery Factors with FVIX and RMW

Table 3A presents the result of fitting several asset-pricing models to returns of the FMax factor from Bali et al. (2017), the FSkew factor from Bali et al. (2019), and a version of FSkew, dubbed FSkewO, based on the expected skewness measure from Boyer et al. (2010), the first paper to show that expected skewness is negatively priced.

The traditional benchmark models, such as the CAPM, the three-factor Fama-French (1993) model, and the Carhart (1997) model, report that all three factors have large and significant alphas, ranging from 49 to 73 bp per month for FMax, from 29 to 41 bp per month for FSkew, and 27 to 34 bp per month for FSkewO (the Carhart alpha of FSkewO is insignificant at 16 bp per month).

Augmenting those models with FVIX, generally reducing them below 15 bp per month with t-statistics below 1.2. The average percentage reduction in the alphas is 72%. The explanatory power of FVIX stems from significantly negative FVIX betas, characteristic of all three lottery/skewness factors. The negative FVIX betas and the ability of FVIX to explain the alphas of the lottery/skewness factors suggests that the Bali et al. (2019) result that FSkew can explain the profitability anomaly can arise because FSkew is picking up aggregate volatility risk captured by FVIX.

Similarly, the two rightmost columns in Table 3A fit the five-factor Fama and French (2015) model and its version augmented with the momentum factor of Carhart (1997) to returns of FMax, FSkew, and FSKewO, and find that controlling for RMW explains the alphas of the three lottery/skewness factors, reducing their alphas to statistically insignificant 12.5-16.5 bp per month. The investment factor (CMA) betas of FSkew and FSkewO are insignificant, but the profitability factor (RMW) beta is large and significant for all three lottery/skewness factors, suggesting that RMW is the driving force behind the five-factor model ability to explain the alphas of FMax, FSkew, and FSKewO.

2.3 Skewness and Lottery Factors Cannot Explain FVIX

Barillas and Shanken (2017) suggest a simple test they call a spanning test to evaluate which of the two competing factors is driving the other. An example would be first putting factor X on the left-hand side and estimating the Fama-French model augmented with factor Y to explain the alpha of X, and flipping the regression over by putting Y on the left-hand side, augmenting the Fama-French model with X and looking at the alpha of Y. Suppose in the example above the first regression yield an insignificant alpha of X (so that we conclude that Y explains X) and the second regression yields a significant alpha of Y (so that we conclude that X cannot fully explain Y). In this case, one can say that Y "spans" X and thus it is Y that is driving X and not the other way around: if investors already trade the Fama-French factors and Y, adding X to their portfolio does not improve their investment opportunity set (because doing so delivers no additional alpha), but if investors already trade the Fama-French factors and X, it still makes sense for them to start trading Y too. So, in this example X is redundant: once you are trading Y, you do not need to trade X; if you are trading X, it makes sense to add Y - and then drop X.

Table 4A puts FVIX on the left-hand side and tries to explain its alpha using the traditional factors and the three lottery/skewness factors. Similar to Table 2 in the paper, Table 4A finds that the traditional benchmark models (the CAPM, the three-factor Fama and French (1993) model, the Carhart (1997) model) cannot explain the alpha of FVIX, estimating it to be in the tight range between -44.5 and -46.8 bp per month with t-statistics exceeding 3.5 in absolute magnitude. Augmenting these models with FSkew and FSkewO reduces the alphas of FVIX by 3-7 bp per month; augmenting the benchmark models with FMax brings about a larger reduction of 7-15 bp per month, but the alphas of FVIX still remain highly statistically significant and exceed, in absolute magnitude, -30 bp per month.

In untabulated results, I also consider the five-factor Fama and French (2015) model and its version augmented with the momentum factor as benchmark models. I find that these models still cannot explain the alpha of FVIX (it is reduced to -30 bp per month, but the t-statistic still exceeds -3). Adding FSkew and FSkewO to these benchmark models does not change the alpha of FVIX, since FSkew and FSkewO are insignificant in the presence of RMW. FMax retains significance if added to the five-factor and six-factor models, but adding it reduces the alpha of FVIX only by 1-2 bp. These results preview the results in Table 5A that evaluates the overlap between RMW and the three lottery/skewness factors.

Combining the results in Tables 3A and 4A results in the spanning test suggested by Barillas and Shanken (2017): Table 3A shows that FVIX can explain the alphas of the three lottery/skewness factors, but Table 4A finds the reverse is not true. Hence, FVIX is driving the lottery factors and their ability (documented by Bali et al., 2019) to explain the profitability anomaly. To put it differently, the three lottery/skewness factors are just proxies for a bigger factor, FVIX.

2.4 Skewness and Lottery Factors Cannot Explain RMW

Table 5A presents the results that complement Table 3A in terms of the spanning test between RMW and the three lottery/skewness factors. Table 5A puts RMW on the left-hand side and uses the traditional benchmark models (the CAPM, the three-factor Fama and French (1993) model, the Carhart (1997) model), as well as their versions augmented with one of the three lottery/skewness factors to explain the alpha of RMW. The traditional benchmark model cannot explain the alpha, confirming the existence of the profitability anomaly - the alpha of RMW ranges from 37.4 to 48.2 bp per month depending on the benchmark model, with t-statistic of at least 2.8.

Adding either of the two skewness factors (FSkew or FSkewO) reduces the RMW alpha by 6-20 bp per month, but leaves it statistically significant. I do observe that RMW has a large and significantly positive skewness beta, but the fact that RMW explains the alphas of FSkew and FSkewO in Table 3A, but neither FSkew nor FSkewO can fully explain the alpha of RMW in Table 5A suggests that RMW spans FSkew and FSkewO and not the other way around.

Adding FMax has a bigger impact on RMW alpha: if FMax is added to the three-factor Fama and French (1993) model or the Carhart (1997) model, the alpha of RMW becomes 21 bp per month and marginally significant, a large change from 37-41 bp per month prior to controlling for FMax. If FMax is added to the CAPM, RMW alpha is even smaller, 18 bp per month, and marginally insignificant. When RMW is used to explain the alpha of FMax in Panel A of Table 3A, the change in the alpha after RMW is added is larger and the remaining alpha of FMax is somewhat smaller and insignificant. Thus, the spanning test of FMax and RMW brings about an inconclusive result, but leans in favor RMW being the driver of FMax rather than the other way around.

To sum up the results in this section, in the horse race between FVIX and the three lottery/skewness factors FVIX comes out on top as the main factor and the three lottery/skewness factors seem to be just manifestations of a broader phenomenon captured by FVIX - aggregate volatility risk. In the horse race between RMW and FSkew/FSkewO, RMW also emerges as the winner and the more broad and important anomaly. The horse race between RMW and FMax is inconclusive, but still favors RMW. Overall, it seems that the true competition is between FVIX explains RMW, and the winner will also be the explanation of why FMax/FSkew/FSkewO are priced.

The competition of FVIX and RMW is the focus of the paper and Table 2 in the paper uses the same spanning test and resolves it in favor of FVIX as the driving factor behind RMW.

3 Alternative Volatility Risk Factors

3.1 Short-Run Volatility, Long-Run Volatility, and FVIX

A theory paper by McQuade (2018) predicts that volatility risk should explain the negative alphas of distressed firms, but comes to this conclusion assuming that it is long-run shocks to volatility that matter. While the economic mechanism in McQuade (2018) is similar to the one in this paper, the empirical prediction is different: the VIX index measures implied volatility of one-month options on S&P 100 and thus predicts short-run, rather than long-run volatility. The ability of FVIX factor to explain the profitability anomaly is thus not fully consistent with the model of McQuade (2018).

In Table 6A, I follow Adrian and Rosenberg (2008) and use Component GARCH (C-GARCH) model for the market return to split market volatility into a short-run and a long-run component. I then form factor-mimicking portfolios for the changes in expected short-run and long-run volatility and denote them SR and LR, respectively.[1] Beyond evaluating which volatility component, short-run or long-run, contributes more to explaining the profitability anomaly, Panel A also tests whether explanatory power of FVIX comes from VIX ability to predict realized volatility or from other VIX components such as risk aversion or variance risk premium, since C-GARCH volatility forecast is related only to the former.

Table 6A looks at the high-minus-low profitability portfolios formed from quintile sorts on the four profitability measures used in Tables 3 and 7 and on retained earnings. The top three rows in Table 6A repeat the CAPM and ICAPM alphas and FVIX betas of these portfolios. The next three rows look at the three-factor model with the market factor,

[1]More details on the C-GARCH model and the factor-mimicking procedure used to form SR and LR are in the Data Appendix.

SR, and LR (described in the previous paragraph) and report the alphas and volatility risk betas of the high-minus-low portfolios. I find that the three-factor model yields the average alpha of 36 bp per month (across the five high-minus-low portfolios), as compared to the average alpha of 57 (18) bp per month from the CAPM (the ICAPM with FVIX).

I also find that all SR betas are significantly negative, which suggests that the high-minus-low portfolios are exposed to short-run volatility risk, but LR betas are either insignificant or significantly positive, indicating no long-run volatility risk. These results are consistent with the analysis in my paper, which explains the profitability anomaly using FVIX (essentially a short-run volatility risk factor), but inconsistent with the prediction of McQuade (2018) that it is exposure to long-run volatility risk that will explain the negative alphas of distressed firms.

The last four rows of Table 6A use SR, LR, and FVIX in one model in order to gauge the overlap between SR and FVIX. The overlap turns out to be strong: when SR and FVIX are used together, either one or the other becomes (marginally) insignificant. However, the comparison of the alphas suggests that FVIX has more information than SR: the model with both SR and FVIX yields the average alpha of 25 bp per month, as compared with the three-factor model (average alpha of 36 bp per month) and the ICAPM with FVIX (average alpha of 18 bp per month). The conclusion that FVIX has more information than SR is further supported by spanning tests similar to Table 2 in the paper (not tabulated for brevity), in which FVIX can explain the alpha of SR, but not the other way around.

The fact that FVIX spans SR and the ICAPM with FVIX explains the profitability anomaly better than the Adrian-Rosenberg model is probably not surprising. When investors form option prices, which are the basis of VIX (implied volatility), investors use multitude of information sources, while C-GARCH models only use the information in market returns to derive market volatility forecast. Yet, the Adrian-Rosenberg model does produce significant loadings of the high-minus-low profitability portfolios on the short-run volatility factor and a significant reduction in the alphas once SR is controlled for, and that suggests that the risk of changes in expected realized volatility (rather than changes in risk aversion or in variance risk premium, which might also be picked by VIX) plays a significant and possibly decisive role in explaining the profitability anomaly.

3.2 Alternative Versions of FVIX

In Table 7A, I consider four modifications of FVIX factor. The first one, FVIX90, omits the first four years of the sample and tests the robustness of the results to excluding the October 19, 1987 outlier, when VIX increased by 113 points in one day (the average absolute daily change in VIX in 1990-2014 was 1.05).

The second modification aims to make FVIX fully tradable. Following the tradition of the factor-mimicking literature, started in Breeden et al. (1989), the preceding analysis forms FVIX running one factor-mimicking regression for the whole sample. On the one hand, the full-sample factor-mimicking regression increases precision of the estimates. On the other hand, one can argue that the full-sample regression uses information unavailable to investors, especially in the early years of the sample. It is not clear if investors indeed had as little information as an econometrician would in the beginning of the sample: presumably, investors were able to estimate expected market volatility and hedge against its movements even before VIX is introduced. Still, in the robustness check I follow a conservative assumption that investors know as much as an econometrician, and form FVIXT using expanding window. 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 then expand the estimation window one month at a time: e.g., in January 1997, I estimate the factor-mimicking regression using data from January 1988 to December 1996 and use its coefficients as portfolio weights to form FVIXT portfolio for January 1997, then I re-estimate the factor-mimicking regression using data from January 1988 to January 1997 and use the slopes to compute returns to FVIXT in February 1997, etc.[2]

The third modification of FVIX, FVIX6, uses as base assets for the factor-mimicking regression six size and book-to-market portfolios from Fama and French (1993). The six portfolios split all firms into two size groups (market cap below and above NYSE median) and three book-to-market groups (bottom 30%, middle 40%, top 30%).

The last modification of FVIX, FVIX500, mimics the newer VIX, which is implied volatility of options on S&P 500 (the version of VIX used in the paper is based on S&P 100 options and currently has ticker VXO). The newer VIX data start in 1990, and the factor-mimicking procedure is the same as the one used for the baseline FVIX (the base assets are quintiles sorted on historical sensitivity to changes in the newer VIX).[3]

Panel A of Table 7A looks at descriptive statistics of the main version of FVIX and the three modifications. I find that the average returns and CAPM alphas of all FVIX versions

[2]The original paper by Ang et al. (2006) suggests a different fix for making FVIX tradable and simultaneously limiting the impact of the October 19, 1987 outlier. Ang et al. run the factor-mimicking regression using daily returns in each month separately and use the coefficients to form FVIX in the next month. Estimating six parameters of the factor-mimicking regression using about 22 daily returns in a month results in imprecise estimates, and I find, repeating their procedure, that the coefficients are indeed very noisy and unstable. Besides, most months do not even have significant volatility shifts for the regression to learn from. Thus, it is not surprising that the rolling window approach in Ang et al. creates FVIX with low factor risk premium.

[3]The new VIX is also non-tradable: one cannot buy or sell it, and technically it is a square root of a variance swap (which is different from volatility swap by Jensen's inequality). VIX is constructed so that it would fluctuate around a constant mean; a truly tradable volatility index will be declining rapidly to reflect its negative price of risk. For example, if one invested \$1000 in FVIX in February 1986, by December 2014 (end of my sample) the sum would dwindle to \$4.64, consistent with -1.34% per month average return of FVIX.

are rather close, with the baseline FVIX being a bit ahead of others, and FVIX6 and FVIX 500 somewhat lagging behind. The marginal advantage of the baseline FVIX is consistent with the factor-mimicking procedure in the paper being optimal: it uses the base assets with the largest spread in VIX sensitivity, uses the maximum number of observations for maximum precision, and the outlier of October 19, 1987 turns out to be an informative one.

FVIXT has the highest Sharpe and appraisal ratios, but otherwise is very close to FVIX90, which suggests lack of material look-ahead bias in FVIX versions that use the full-sample factor-mimicking regression. It is also expected that FVIX and FVIX6 have higher variance, skewness, and kurtosis, as they include the October 19, 1987 outlier.

The last two columns of Panel A present five-factor Fama-French alphas and their t-statistics, revealing that the inability of the five-factor model (and RMW in particular) to explain FVIX alpha does not depend on whether the October 19, 1987 outlier is in the sample and whether FVIX is fully tradable. FVIX6 stands out in this regard with a twice smaller and marginally significant alpha, which is to be expected given the fact that FVIX6 uses the same base assets as the ones used to construct SMB and HML. FVIX500 has somewhat smaller alpha than FVIX90 (the factor that uses the same sample period, but mimics the old VIX), but the t-statistics of FVIX90 and FVIX500 alphas are barely different.

Panel B presents correlations between the factors, with simple correlations above the main diagonal and partial correlations conditional on the market factor below the diagonal. Simple correlations are between 0.97 and 0.99, but their extreme magnitude is partly driven by the fact that all versions of FVIX are tightly negatively related to the market return, just as change in VIX is. Controlling for the market return, fully tradable FVIXT is still closely correlated with FVIX (0.85) and FVIX90 (0.92), which again suggests that the dynamics of the baseline FVIX are hardly affected by any potential look-ahead bias. FVIX6 is less tightly correlated with the other three versions of FVIX (correlations range between 0.59 and 0.73), which suggests that the choice of the base assets matters.

Panel C starts with repeating the results in Tables 3 and 7 in the paper and reports in first three rows the CAPM alphas, ICAPM alphas, and FVIX betas of the high-minus-low profitability portfolios formed from quintile sorts on the four profitability measures used in Tables 3 and 7 in the paper and on retained earnings.

The fourth and fifth row re-estimate the ICAPM replacing the baseline FVIX used throughout the paper with FVIX90 and find that omitting the early years (including the October 19, 1987 outlier) from the sample slightly reduces the explanatory power of FVIX. Compared to the second row, the alphas in the fourth row are 1 to 16 bp per month larger.

The sixth and seventh row re-run the ICAPM with FVIXT instead of FVIX. The alphas in row six are similar to the ones in row four: in three cases, the alpha in row six is by 5 to 13 bp per month greater, in two cases it is by 5 to 14 bp smaller than in row four. The comparison suggests that while the ICAPM with FVIXT indeed works slightly worse than the ICAPM with FVIX, the cause is not the potential look-ahead bias. Rather, since the ICAPM with FVIXT performs just as well as the ICAPM with FVIX90, the difference between ICAPM with FVIXT and ICAPM with FVIX is caused by the loss of the early years of the sample to the learning sample in the case of FVIXT.

Rows eight and nine of Panel C present the ICAPM with FVIX6, which performs similarly to the ICAPM with FVIX90 and ICAPM with FVIXT, but marginally worse than ICAPM with FVIX. Finally, rows ten and eleven present the ICAPM with FVIX500 and report results that are very similar to the ones from the ICAPM with FVIX90: the alphas in row ten fall within 10 bp of those in row four.

Overall, while Panel C suggests that the procedure the paper follows to construct FVIX is indeed optimal and yields the best performance of FVIX as an explanatory factor for the profitability anomaly, small perturbations to the procedure leave the results in the paper qualitatively similar.

Taken together, the first column of Panel C and the last two columns of Panel A also confirm the result of Table 2 in the paper using alternative versions of FVIX: no matter which version of FVIX one uses, FVIX can explain RMW, but not the other way around.[4]

Panel D of Table 7A repeats Panel B of Table 2 in the paper and verifies that FVIXT can explain the alphas of RMW. The sample period in Panel D is 1991-2014 (based on FVIXT availability), thus the CAPM/Fama-French/Carhart alphas in Panel D of Table 7A are a few bp per month larger than in Panel B of Table 2. In Panel D of Table 7A, RMW loads significantly and negatively on FVIXT irrespective of the factor model FVIXT is added to, and after controlling for FVIX the alphas of RMW are only 2-8 bp larger than in Panel B of Table 2 in the paper. I conclude that the ability of FVIX to explain RMW (but not the other way around, see Panel A of Table 7A) is not coming from the fact that FVIX uses the full-sample regression for factor mimicking.

4 Profitability Anomaly and Conditional CAPM

O'Doherty (2012) uses the logic in Johnson (2004) that increased volatility makes the beta of a levered firm smaller and shows that Conditional CAPM (CCAPM) reduces the alpha

[4]Strictly speaking, the quintile alpha spread from profitability sorts and RMW alpha are different, with the former being bigger and harder to explain, as Tables 2 and 3 in the paper show. RMW buys/short top/bottom 30% firms in terms of profitability, does that separately for firms above and below median size, and then averages the returns. In untabulated findings, I confirm that FVIXT can explain the alpha of RMW, reducing its alpha to statistically insignificant 18 bp and 19 bp per month in the CAPM and Carhart model augmented with FVIXT.

differential between healthy and distressed firms to still large, but statistically insignificant values. Since profitability and distress are correlated in cross-section, as Panel A of Table 1 shows, CCAPM can contribute to explaining the profitability anomaly.

My paper argues that the volatility risk factor is needed and while the channel in Johnson (2004) also predicts smaller losses to distressed/unprofitable firms in recessions (lower market beta implies lower discount rates and higher prices), there is a simpler and potentially stronger channel that makes distressed/unprofitable firms a hedge against volatility risk: equity of those firms can be thought of as a call option on the assets, and the value of an option increases in volatility, all else equal.

Table 8A fits CCAPM to the five high-minus-low portfolios from Table 6A. Panel A of Table 8A uses the four standard conditioning variables (see, e.g., Petkova and Zhang, 2005, and Boguth et al., 2011) - default spread (DEF), dividend yield of the market portfolio (DIV), Treasury bill rate (TB), and term premium (TERM).[5]

Panel A1 uses the same four variables to predict the market risk premium, divides the sample into recessions and expansions based on whether the market risk premium forecast is above or below the in-sample median, and averages conditional market betas of the high-minus-low portfolios across expansions and recessions. Consistent with the prediction of Johnson (2004) and O'Doherty (2012) about distressed firms, the high-minus-low profitability portfolios exhibit strongly countercyclical betas, which increase in recessions by 0.103 to 0.471 (average 0.28), which can contribute to explaining the positive alphas of the high-minus-low portfolios (the profitability anomaly).

Panel A2 looks at the CAPM, CCAPM, and ICAPM alphas of these portfolios and finds that CCAPM alphas (average 0.38 bp per month) fall right in the middle between

[5]Detailed definitions of all conditioning variables are in Data Appendix.

CAPM (average 0.57 bp per month) and ICAPM (average 0.18 bp per month) alphas and remain significant or marginally significant. I conclude that while the explanation of the distress risk puzzle in Johnson (2004) and O'Doherty (2012) contributes to understanding the profitability anomaly, my explanation of the profitability anomaly encompasses their theory and has roughly twice the explanatory power.

In the last two columns of Panel A2, I perform a horse race between the two explanations by adding FVIX to the CCAPM (and thus creating a conditional ICAPM, or CICAPM) and report the alphas and FVIX betas. The most important observation is that the alphas, on average, are not different from the ICAPM alphas (18 bp vs. 14 bp per month average). In some cases (gross profitability and retained earnings), CICAPM beats ICAPM by 12-15 bp per month, in some cases (operating and cash-based profitability), the reverse happens, but in all cases it is a comparison of two insignificant numbers. I conclude that, as my explanation of the profitability anomaly suggests, the effect of making the market beta conditional is subsumed by FVIX.

Another evidence of the overlap between the conditional beta effect is that compared to ICAPM, FVIX betas decline by roughly one-third (but stay highly significant) after the market beta is made conditional. Again, since the CICAPM generates roughly the same alphas as the usual ICAPM, the overlap suggests that FVIX and the conditioning variables carry similar information, and FVIX spans the conditioning variables in this application.

Panels B and C of Table 8A repeat the analysis in Panel A by adding the VIX index to the conditioning variables (Panel B) and also adding lagged market return and historical market beta of the portfolio (Panel C). The latter two variables are used in O'Doherty (2012) following Boguth et al. (2011), who suggest using them to capture volatility timing.

Both Panel B and C find that when the four standard variables are controlled for, the additional volatility-related variables are not helpful in explaining the profitability anomaly: both CCAPM and CICAPM betas are very similar in Panels A, B, and C, and the countercyclicality of market beta is somewhat weaker in Panels B and C compared to Panel A. These results do not imply that the relation between market beta and market volatility is not important in explaining the profitability anomaly, but rather that this relation matters to the extent that it captures the relation between market beta and the state of the economy, and the latter is adequately captured by the four standard conditioning variables.

5 Distress Risk Puzzle and Average IVol

The aggregate volatility risk explanation of the profitability anomaly works through the vega of equity. The greater is the vega, the stronger is the positive effect of volatility on distressed equity value. The positive effect can come from increases in market volatility, idiosyncratic volatility, or both. As a referee pointed out, FVIX can be picking up some effects of average IVol as well, since VIX and average IVol in the market are correlated.

Barinov and Chabakauri (2022) show that average IVol is priced, as was first suggested by Petkova and Chen (2012) and Herskovic et al. (2016). Barinov and Chabakauri present a theoretical model, in which average IVol factor, along with FVIX, explains the value effect, and then construct an empirical average IVol factor, FIVol, which explains the value effect in the data as well.

In Table 9A, I use the volatility factor model (the market factor, FVIX, and FIVol) from Barinov and Chabakauri (2022) to explain the profitability effect and its cross-section. Using FVIX and FIVol factors together alleviates the concern that FVIX can be picking up effects of average IVol.

Panels A and B look at quintile sorts on profitability and gross profitability, respectively, and finds that FIVol does not help in explaining the profitability effect. This fact is not surprising. As Fama and French (1995) point out, growth firms are usually profitable, and value firms are not. Since Barinov and Chabakauri (2022) find that FIVol explains the value effect, the high-minus-low profitability portfolio should mechanically load positively on FIVol rather than negatively.

Panels C and D of Table 9A look at alphas of the high-minus-low profitability portfolios formed separately in each O-score quintile, as in Table 5 in the paper. In Panel C, we find that the high-minus-low portfolio loads negatively on FIVol in the top two O-score quintile. However, the impact of FIVol is not large: adding FVIX to the two-factor ICAPM (market plus FVIX) makes the high-minus-low portfolio alpha decline by about 20 bp per month (from an already insignificant value). Panel D does not reveal any significant loadings of the high-minus-low portfolio (based on gross profitability) on FIVol.

Panels E and F of Table 9A look at alphas of the high-minus-low profitability portfolios formed separately in each IVol quintile, as in Table 6 in the paper. In both panels, the high-minus-low profitability portfolios load negatively on FIVol in the top IVol quintile, and the difference between these loadings and the FIVol loadings of the high-minus-low profitability portfolios in the bottom IVol quintile is also significant. The effect of FIVol control on the alpha of the high-minus-low profitability portfolios in the top IVol quintile is at 25-40 bp per month, but the alphas change from insignificant to insignificant (though lower) values when FIVol is added.

The most important message from Table 9A is that controlling for FIVol does not materially change FVIX betas. Hence, the explanatory power of FVIX does not come from FVIX picking up average IVol effects.

6 Profitability Anomaly and Duration

A long string of papers, starting with Dechow et al. (2004) and Lettau and Wachter (2007), shows that equity duration is negatively priced. Low-duration firms (with a large fraction of firm value coming from close-in-time cash flows) tend to be profitable firms and value firms. A recent paper by Gonçalves (2021) shows that in cross-sectional regressions, equity duration subsumes both the value effect and the profitability anomaly.

Since FVIX also appears to explain both the value effect (see Barinov and Chabakauri, 2022) and the profitability anomaly, it is natural to wonder if FVIX and the duration effect in returns overlap. In Table 10A, I perform a spanning test in the spirit of Barillas and Shanken (2017) by running the duration-based factor, DUR, on FVIX (Panel A) and then FVIX on the duration factor (Panel B). DUR is the value-weighted return spread between the bottom and top duration deciles.[6]

Panel A shows that the duration factor indeed is exposed to aggregate volatility risk: irrespective of which benchmark model I add FVIX to, the FVIX beta of DUR is negative and significant. The effect of FVIX on the alpha of DUR is not large: FVIX explains 10-24 bp per month of the alpha (which, in turn, hovers between 38 and 68 bp per month). In many cases, however, adding FVIX makes the alpha of DUR either marginally significant at the 10% level or insignificant. For example, consistent with Gonçalves (2021), DUR has a five-factor alpha of 37.6 bp per month, t-statistic 2.08, and Panel A of Table 10A reports that adding FVIX to the five-factor Fama and French (2015) model reduces the alpha of DUR to 27.6 bp per month, t-statistic 1.48. I conclude that there is a significant overlap between FVIX and DUR, but at least according to point estimates there is a significant

[6] Duration decile returns are from the webpage of Andrei Gonçalves, https://andreigoncalves.com/research/.

part of DUR that is not explained by aggregate volatility risk.

Panel B of Table 10A shows that the ability of DUR to explain FVIX alpha is even smaller. FVIX loads on DUR negatively, but the loadings are numerically small and usually significant only at the 10% level. Adding DUR to benchmark asset-pricing model results in FVIX alpha declining by only 1.5-5 bp per month and staying highly significant.

Overall, Table 10A suggests that DUR and FVIX are two very distinct factors with relatively small overlap.

In Table 11A, I perform a horse race between DUR and FVIX by using both to explain the alpha of the RMW factor. I find that RMW loads positively and significantly on DUR, which is consistent with Gonçalves (2021), but controlling for DUR reduces the alpha of RMW by only 7-10 bp per month and leaves it statistically significant. The latter evidence is not consistent with the finding of Gonçalves (2021) that duration subsumes profitability in cross-sectional regressions. On the one hand, one can view this inconsistency as a covariance vs. characteristic test: as a firm characteristic, duration subsumes profitability, but covariance with DUR, the duration-based factor, does not matter as much. On the other hand, Gonçalves (2021) suggests an ICAPM-style explanation of the duration effect on returns, based on reinvestment risk. If duration picks up risk, then it is the covariance with DUR that should matter, and DUR should be at least as useful in time-series regressions in terms of explaining the profitability anomaly as duration, a firm characteristic, is in cross-sectional regressions.

Another message from Table 11A is that FVIX and DUR have little overlap, just as Table 10A suggests. When both are used to explain RMW alpha, both remain significant and FVIX/DUR betas of RMW do not change much when the other factor is controlled for.

I conclude from Tables 10A and 11A that it is unlikely that FVIX picks up duration effects. The duration-based explanation of the profitability anomaly in Gonçalves (2021) seems largely orthogonal to the aggregate volatility risk explanation in my paper.

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Table 1A. Frequency of Credit Rating Upgrades/Downgrades during Recessions

The table presents the slopes from regressions of average frequency of credit rating upgrades (Panel A) or credit rating downgrades (Panel B) on the constant and the recession dummy (one in a recession, zero otherwise). The frequency of upgrades/downgrades is averaged separately within each profitability quintile. The quintiles are formed using NYSE (exchcd=1) breakpoints and are rebalanced annually. ROE is net income before extraordinary items (Compustat ib item) divided by book value of equity (ceq plus txdb). Gross profitability is total revenue (sale) minus cost of goods sold (cogs) divided by book value of equity (ceq plus txdb). Operating profitability is total revenue (revt) minus cost of goods sold (cogs) minus SG&A (xsga) plus R&D expenses (xrd) if available, divided by total assets (at) from the previous year. Cash-based operating profitability deducts accruals from the denominator of operating profitability above. Following Ball et al. (2016), accruals are defined as change in accounts receivable (rect) plus change in inventory (invt) plus change in prepaid expenses (xpp) minus in deferred revenue (drc plus drlt) minus change in accounts payable (ap). Credit rating is Standard and Poor's rating (splticrm variable in the Compustat adsprate file). Recession is defined using NBER recession dates (Panels A1 and B1) or as periods when expected market risk premium is above its in-sample median. Expected market risk premium is the fitted value from regression of market returns on dividend yield, default premium, one-month Treasury bill rate, and term premium. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2014. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Panel A. Additional Frequency of Credit Rating Upgrades during Recessions

Panel A1. Recessions as Defined by NBER

	Low	Prof2	Prof3	Prof4	High	H-L
ROE	1.36%	1.15%	0.88%	0.89%	0.59%	-0.77%
t-stat	*3.71*	*3.73*	*2.24*	*3.94*	*2.07*	*-2.79*
GProf	0.85%	0.87%	1.30%	0.99%	0.71%	-0.13%
t-stat	*2.71*	*2.21*	*3.89*	*4.73*	*2.45*	*-0.49*
OProf	1.51%	1.16%	0.91%	0.87%	0.36%	-1.15%
t-stat	*3.41*	*3.08*	*2.55*	*4.85*	*1.24*	*-3.36*
CashProf	1.59%	0.97%	0.90%	0.78%	0.66%	-0.93%
t-stat	*3.84*	*2.29*	*4.02*	*2.68*	*2.12*	*-2.85*

Panel A2. Recessions based on Market Risk Premium

	Low	GProf2	GProf3	GProf4	High	H-L
ROE	0.08%	-0.27%	-0.22%	-0.26%	-0.28%	-0.36%
t-stat	*0.40*	*-1.61*	*-1.42*	*-1.85*	*-2.04*	*-2.15*
GProf	0.11%	-0.20%	-0.24%	-0.29%	-0.24%	-0.34%
t-stat	*0.59*	*-1.29*	*-1.37*	*-2.12*	*-1.57*	*-1.75*
OProf	0.10%	-0.30%	-0.13%	-0.31%	-0.27%	-0.37%
t-stat	*0.52*	*-1.70*	*-0.85*	*-2.48*	*-1.80*	*-2.28*
CashProf	-0.02%	-0.18%	-0.07%	-0.29%	-0.30%	-0.29%
t-stat	*-0.08*	*-1.08*	*-0.52*	*-2.05*	*-2.24*	*-1.62*

Panel B. Additional Frequency of Credit Rating Downgrades during Recessions

Panel B1. Recessions as Defined by NBER

	Low	Prof2	Prof3	Prof4	High	H-L
ROE	-0.75%	-0.83%	-0.82%	-0.88%	-0.79%	-0.04%
t-stat	*-2.18*	*-2.23*	*-2.16*	*-2.44*	*-2.15*	*-0.19*
GProf	-0.81%	-0.79%	-0.80%	-0.99%	-0.65%	0.16%
t-stat	*-2.14*	*-2.05*	*-2.11*	*-2.60*	*-1.59*	*0.69*
OProf	-0.77%	-0.55%	-0.85%	-1.12%	-0.94%	-0.17%
t-stat	*-2.07*	*-1.33*	*-2.36*	*-3.18*	*-2.32*	*-0.77*
CashProf	-0.57%	-0.76%	-0.89%	-0.99%	-0.94%	-0.37%
t-stat	*-1.16*	*-2.04*	*-2.51*	*-2.77*	*-2.42*	*-1.02*

Panel B2. Recessions based on Market Risk Premium

	Low	GProf2	GProf3	GProf4	High	H-L
ROE	0.67%	0.45%	0.50%	0.50%	0.48%	-0.19%
t-stat	*1.23*	*0.83*	*0.93*	*0.90*	*0.84*	*-0.98*
GProf	0.41%	0.38%	0.60%	0.54%	0.60%	0.18%
t-stat	*0.76*	*0.70*	*1.08*	*0.98*	*1.06*	*1.03*
OProf	0.56%	0.42%	0.40%	0.55%	0.70%	0.14%
t-stat	*1.01*	*0.78*	*0.74*	*1.03*	*1.23*	*0.63*
CashProf	0.48%	0.69%	0.66%	0.45%	0.33%	-0.16%
t-stat	*0.87*	*1.28*	*1.20*	*0.83*	*0.59*	*-0.79*

Table 2A. Omitting Past and Future Downgrades

The table omits from the sample all credit rating downgrade events that happened six month before and six month after portfolio formation and then reports value-weighted alphas from the CAPM and the ICAPM with the market factor and FVIX, as well as FVIX betas from the ICAPM, across ROE (Panel A) , gross profitability (Panel B), operating profitability (Panel C), and cash-based profitability (Panel D) quintiles. The quintiles are formed using NYSE (exchcd=1) breakpoints and are rebalanced annually. Profitability is net income before extraordinary items (Compustat ib item) divided by book value of equity (ceq plus txdb). Gross profitability is total revenue (sale) minus cost of goods sold (cogs) divided by book value of equity (ceq plus txdb). Operating profitability is total revenue (revt) minus cost of goods sold (cogs) minus SG&A (xsga) plus R&D expenses (xrd) if available, divided by total assets (at) from the previous year. Cash-based operating profitability deducts accruals from the denominator of operating profitability above. Following Ball et al. (2016), accruals are defined as change in accounts receivable (rect) plus change in inventory (invt) plus change in prepaid expenses (xpp) minus in deferred revenue (drc plus drlt) minus change in accounts payable (ap). Credit rating is Standard and Poor's rating (splticrm variable in the Compustat adsprate file). 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 2014. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Panel A. ROE of Fama and French (2006)

	Low	Prof2	Prof3	Prof4	High	H-L
$\boldsymbol{\alpha}_{CAPM}$	-0.302	0.071	0.215	0.011	0.211	0.514
t-stat	*-1.74*	*0.76*	*2.67*	*0.14*	*2.43*	*2.36*
$\boldsymbol{\alpha}_{ICAPM}$	0.128	0.197	0.131	-0.009	0.094	-0.033
t-stat	*0.82*	*1.99*	*1.72*	*-0.11*	*0.94*	*-0.15*
$\boldsymbol{\beta}_{FVIX}$	0.912	0.266	-0.179	-0.041	-0.248	-1.161
t-stat	*3.68*	*2.56*	*-2.00*	*-0.75*	*-2.80*	*-3.78*

Panel B. Gross Profitability of Novy-Marx (2013)

	Low	GProf2	GProf3	GProf4	High	H-L
$\boldsymbol{\alpha}_{CAPM}$	-0.286	0.161	0.061	0.202	0.259	0.545
t-stat	*-1.99*	*1.66*	*0.57*	*2.48*	*2.80*	*2.72*
$\boldsymbol{\alpha}_{ICAPM}$	-0.026	0.212	0.117	0.074	0.114	0.139
t-stat	*-0.20*	*1.95*	*1.11*	*0.95*	*1.16*	*0.73*
$\boldsymbol{\beta}_{FVIX}$	0.552	0.109	0.118	-0.272	-0.309	-0.860
t-stat	*2.80*	*1.33*	*1.00*	*-3.77*	*-2.85*	*-2.93*

Panel C. Operating Profitability of Ball et al. (2015)

	Low	Prof2	Prof3	Prof4	High	H-L
$\boldsymbol{\alpha}_{CAPM}$	-0.148	0.295	0.188	0.190	0.085	0.232
t-stat	*-1.35*	*2.69*	*1.79*	*2.39*	*0.74*	*1.40*
$\boldsymbol{\alpha}_{ICAPM}$	0.065	0.180	0.009	0.046	0.159	0.094
t-stat	*0.62*	*1.51*	*0.08*	*0.50*	*1.42*	*0.55*
$\boldsymbol{\beta}_{FVIX}$	0.452	-0.245	-0.379	-0.306	0.158	-0.294
t-stat	*5.76*	*-1.64*	*-2.53*	*-2.92*	*1.38*	*-2.74*

Panel D. Cash-Based Profitability of Ball et al. (2016)

	Low	GProf2	GProf3	GProf4	High	H-L
$\boldsymbol{\alpha}_{CAPM}$	-0.206	0.146	0.196	0.282	0.099	0.305
t-stat	*-1.82*	*1.18*	*2.22*	*3.30*	*0.91*	*2.06*
$\boldsymbol{\alpha}_{ICAPM}$	0.033	0.022	0.067	0.129	0.152	0.120
t-stat	*0.32*	*0.17*	*0.77*	*1.40*	*1.45*	*0.80*
$\boldsymbol{\beta}_{FVIX}$	0.507	-0.264	-0.275	-0.325	0.115	-0.393
t-stat	*4.41*	*-1.16*	*-3.63*	*-2.88*	*1.16*	*-4.72*

Table 3A. Explaining Returns to Lottery and Skewness Factors with FVIX and RMW

The table presents estimates of factor models fitted to returns to the FMax factor from Bali et al. (2017) in Panel A, the FSkew factor from Bali et al. (2019) in Panel B, and a similar FSkewO factor that is based on expected skewness measure from Boyer et al. (2010). FMax (FSkew) buys/shorts firms in the top/bottom 30% in terms of maximum return (expected skewness) in the past month. The returns to the long-short strategy are value-weighted and computed separately for small (below NYSE marker cap median) and large (above median) firms, and then averaged. The sorts on maximum/expected skewness are independent of size and use NYSE breakpoints. The maximum return used to form FMax is the average of the five largest (most positive) daily returns within a month. Expected skewness used to form FSkew is fitted value from cross-sectional regression that predicts idiosyncratic skewness in months t+1 to t+60 using explanatory variables in period t, as described in Bali et al. (2019). Expected skewness used to form FSkewO uses a different list of explanatory variables described in Boyer et al. (2010). The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2014.

Panel A. Explaining Returns of the Lottery Factor (FMax)

	Raw	**CAPM**	**ICAPM**	**FF**	**FF4**	**Carhart**	**5-factor**	**FF5**	**FF6**
$\boldsymbol{\alpha}$	0.318	0.730	0.087	0.557	0.145	0.486	0.062	0.165	0.145
t-stat	*1.31*	*3.93*	*0.42*	*3.56*	*1.04*	*3.06*	*0.44*	*1.41*	*1.19*
$\boldsymbol{\beta}_{MKT}$		-0.628	-2.456	-0.466	-1.732	-0.444	-1.724	-0.357	-0.351
t-stat		*-8.50*	*-4.30*	*-6.45*	*-5.56*	*-7.21*	*-5.54*	*-7.33*	*-8.10*
$\boldsymbol{\beta}_{SMB}$				-0.470	-0.318	-0.475	-0.321	-0.295	-0.300
t-stat				*-5.75*	*-5.06*	*-5.40*	*-4.85*	*-5.09*	*-4.97*
$\boldsymbol{\beta}_{HML}$				0.508	0.442	0.538	0.474	0.195	0.220
t-stat				*3.74*	*3.79*	*4.44*	*4.71*	*1.57*	*2.15*
$\boldsymbol{\beta}_{Mom}$						0.089	0.098		0.040
t-stat						*1.26*	*1.61*		*0.63*
$\boldsymbol{\beta}_{FVIX}$			-1.371		-0.924		-0.936		
t-stat			*-3.45*		*-4.40*		*-4.41*		
$\boldsymbol{\beta}_{CMA}$								0.428	0.406
t-stat								*3.78*	*3.99*
$\boldsymbol{\beta}_{RMW}$								0.650	0.637
t-stat								*11.0*	*10.5*

Panel B. Explaining Returns to Bali et al. (2019) Skewness Factor (FSkew)

	Raw	CAPM	ICAPM	FF	FF4	Carhart	5-factor	FF5	FF6
$\boldsymbol{\alpha}$	0.265	0.406	0.103	0.379	0.196	0.288	0.098	0.137	0.094
t-stat	*1.67*	*2.73*	*0.63*	*2.77*	*1.46*	*2.11*	*0.74*	*0.91*	*0.64*
$\boldsymbol{\beta}_{MKT}$		-0.215	-1.038	-0.153	-0.670	-0.125	-0.661	-0.086	-0.072
t-stat		*-3.90*	*-5.14*	*-3.06*	*-3.73*	*-2.79*	*-3.84*	*-2.03*	*-1.73*
$\boldsymbol{\beta}_{SMB}$				-0.321	-0.260	-0.327	-0.264	-0.207	-0.217
t-stat				*-5.24*	*-4.33*	*-5.08*	*-4.25*	*-3.17*	*-3.36*
$\boldsymbol{\beta}_{HML}$				0.089	0.061	0.127	0.099	-0.099	-0.044
t-stat				*1.01*	*0.68*	*1.59*	*1.22*	*-1.14*	*-0.51*
$\boldsymbol{\beta}_{Mom}$						0.114	0.116		0.086
t-stat						*2.38*	*2.54*		*2.14*
$\boldsymbol{\beta}_{FVIX}$			-0.617		-0.377		-0.392		
t-stat			*-4.14*		*-2.86*		*-3.11*		
$\boldsymbol{\beta}_{CMA}$								0.243	0.195
t-stat								*1.79*	*1.51*
$\boldsymbol{\beta}_{RMW}$								0.416	0.388
t-stat								*4.39*	*4.18*

Panel C. Explaining Returns to Boyer et al. (2010) Skewness Factor (FSkewO)

	Raw	CAPM	ICAPM	FF	FF4	Carhart	5-factor	FF5	FF6
$\boldsymbol{\alpha}$	0.219	0.340	0.110	0.270	0.131	0.163	0.015	0.125	0.063
t-stat	*1.74*	*2.82*	*0.93*	*2.51*	*1.19*	*1.41*	*0.13*	*1.06*	*0.54*
$\boldsymbol{\beta}_{MKT}$		-0.183	-0.816	-0.121	-0.524	-0.087	-0.514	-0.087	-0.067
t-stat		*-4.27*	*-4.10*	*-3.44*	*-4.71*	*-3.02*	*-4.56*	*-3.31*	*-2.40*
$\boldsymbol{\beta}_{SMB}$				-0.173	-0.125	-0.180	-0.130	-0.044	-0.060
t-stat				*-4.64*	*-3.38*	*-4.07*	*-3.30*	*-1.08*	*-1.68*
$\boldsymbol{\beta}_{HML}$				0.204	0.183	0.250	0.228	0.151	0.230
t-stat				*2.58*	*2.35*	*3.34*	*3.20*	*2.77*	*4.32*
$\boldsymbol{\beta}_{Mom}$						0.135	0.137		0.124
t-stat						*2.88*	*2.91*		*3.02*
$\boldsymbol{\beta}_{FVIX}$			-0.475		-0.295		-0.312		
t-stat			*-3.41*		*-3.71*		*-3.79*		
$\boldsymbol{\beta}_{CMA}$								-0.074	-0.142
t-stat								*-0.64*	*-1.62*
$\boldsymbol{\beta}_{RMW}$								0.402	0.361
t-stat								*5.92*	*7.17*

Table 4A. Explaining Returns to FVIX with Lottery and Skewness Factors

The table presents estimates of CAPM, Fama and French (1993) three-factor model, and Carhart (1997) model fitted to returns to the FVIX factor. FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. The models are also augmented with the FMax factor from Bali et al. (2017) in Panel A, the FSkew factor from Bali et al. (2019) in Panel B, and a similar FSkewO factor that is based on expected skewness measure from Boyer et al. (2010). FMax (FSkew) buys/shorts firms in the top/bottom 30% in terms of maximum return (expected skewness) in the past month. The returns to the long-short strategy are value-weighted and computed separately for small (below NYSE marker cap median) and large (above median) firms, and then averaged. The sorts on maximum/expected skewness are independent of size and use NYSE breakpoints. The maximum return used to form FMax is the average of the five largest (most positive) daily returns within a month. Expected skewness used to form FSkew is fitted value from cross-sectional regression that predicts idiosyncratic skewness in months t+1 to t+60 using explanatory variables in period t, as described in Bali et al. (2019). Expected skewness used to form FSkewO uses a different list of explanatory variables described in Boyer et al. (2010). The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2014.

	Raw	**CAPM**	**+Max**	**+Skew**	**+Skew**	**FF3**	**+Max**	**+Skew**	**+Skew**	**Carhart**	**+Max**	**+Skew**	**+Skew**
$\boldsymbol{\alpha}$	-1.342	-0.468	-0.315	-0.413	-0.400	-0.445	-0.337	-0.415	-0.412	-0.453	-0.360	-0.428	-0.429
t-stat	*-4.28*	*-4.47*	*-3.14*	*-4.13*	*-3.94*	*-3.69*	*-3.14*	*-3.55*	*-3.58*	*-3.68*	*-3.42*	*-3.61*	*-3.70*
$\boldsymbol{\beta}_{MKT}$		-1.333	-1.471	-1.364	-1.371	-1.370	-1.464	-1.383	-1.385	-1.367	-1.461	-1.379	-1.380
t-stat		*-36.0*	*-35.2*	*-42.6*	*-38.8*	*-32.8*	*-36.8*	*-35.8*	*-35.3*	*-32.1*	*-36.5*	*-34.9*	*-34.5*
$\boldsymbol{\beta}_{SMB}$						0.165	0.065	0.138	0.143	0.165	0.054	0.135	0.138
t-stat						*4.72*	*2.21*	*3.51*	*4.27*	*4.89*	*2.04*	*3.64*	*4.59*
$\boldsymbol{\beta}_{HML}$						-0.071	0.019	-0.064	-0.045	-0.068	0.039	-0.057	-0.031
t-stat						*-1.32*	*0.40*	*-1.18*	*-0.84*	*-1.30*	*0.94*	*-1.08*	*-0.59*
$\boldsymbol{\beta}_{Mom}$										0.010	0.040	0.020	0.030
t-stat										*0.58*	*2.71*	*1.27*	*1.48*
$\boldsymbol{\beta}_{FMax}$			-0.203				-0.184				-0.199		
t-stat			*-7.34*				*-6.10*				*-8.02*		
$\boldsymbol{\beta}_{FSkew}$				-0.142				-0.083				-0.090	
t-stat				*-5.31*				*-2.75*				*-2.99*	
$\boldsymbol{\beta}_{FSkewO}$					-0.206				-0.127				-0.149
t-stat					*-3.49*				*-3.50*				*-3.97*

Table 5A. Explaining Returns to RMW with Lottery and Skewness Factors

The table presents estimates of CAPM, Fama and French (1993) three-factor model, and Carhart (1997) model fitted to returns to the RMW (profitability) factor from Fama and French (2015). The models are also augmented with the FMax factor from Bali et al. (2017) in Panel A, the FSkew factor from Bali et al. (2019) in Panel B, and a similar FSkewO factor that is based on expected skewness measure from Boyer et al. (2010). FMax (FSkew/RWM) buys/shorts firms in the top/bottom 30% in terms of maximum return (expected skewness/profitability) in the past month. The returns to the long-short strategy are value-weighted and computed separately for small (below NYSE marker cap median) and large (above median) firms, and then averaged. The sorts on maximum/expected skewness are independent of size and use NYSE breakpoints. The maximum return used to form FMax is the average of the five largest (most positive) daily returns within a month. Expected skewness used to form FSkew is fitted value from cross-sectional regression that predicts idiosyncratic skewness in months t+1 to t+60 using explanatory variables in period t, as described in Bali et al. (2019). Expected skewness used to form FSkewO uses a different list of explanatory variables described in Boyer et al. (2010). The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2014.

	Raw	**CAPM**	**+Max**	**+Skew**	**+Skew**	**FF3**	**+Max**	**+Skew**	**+Skew**	**Carhart**	**+Max**	**+Skew**	**+Skew**
$\boldsymbol{\alpha}$	0.362	0.482	0.179	0.351	0.279	0.413	0.213	0.333	0.291	0.374	0.215	0.316	0.299
t-stat	*2.41*	*3.35*	*1.56*	*2.65*	*2.11*	*3.05*	*2.02*	*2.66*	*2.33*	*2.84*	*2.04*	*2.55*	*2.46*
$\boldsymbol{\beta}_{MKT}$		-0.184	0.090	-0.115	-0.075	-0.102	0.073	-0.069	-0.047	-0.089	0.072	-0.064	-0.049
t-stat		*-3.84*	*1.61*	*-3.10*	*-2.15*	*-2.18*	*1.61*	*-1.62*	*-1.22*	*-2.19*	*1.63*	*-1.68*	*-1.30*
$\boldsymbol{\beta}_{SMB}$						-0.309	-0.123	-0.241	-0.231	-0.312	-0.122	-0.245	-0.228
t-stat						*-3.29*	*-1.85*	*-2.62*	*-2.71*	*-3.20*	*-1.97*	*-2.71*	*-2.88*
$\boldsymbol{\beta}_{HML}$						0.208	0.042	0.190	0.116	0.225	0.040	0.199	0.109
t-stat						*2.26*	*0.55*	*2.28*	*1.55*	*2.58*	*0.61*	*2.57*	*1.81*
$\boldsymbol{\beta}_{Mom}$										0.048	-0.004	0.025	-0.014
t-stat										*1.02*	*-0.09*	*0.54*	*-0.31*
$\boldsymbol{\beta}_{FMax}$			0.404				0.341				0.342		
t-stat			*4.95*				*4.64*				*4.79*		
$\boldsymbol{\beta}_{FSkew}$				0.324				0.211				0.203	
t-stat				*3.96*				*4.32*				*3.91*	
$\boldsymbol{\beta}_{FSkewO}$					0.598				0.453				0.463
t-stat					*5.06*				*8.70*				*7.81*

Table 6A. Alternative Risk Factors

The table presents alphas and volatility risk betas from the four models below:

$$\begin{aligned}
\text{CAPM}: \quad & Ret_t - RF_t && = \alpha_{CAPM} + \beta_{MKT} \cdot (MKT_t - RF_t) && (1)\\
\text{ICAPM}: \quad & Ret_t - RF_t && = \alpha_{ICAPM} + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t && (2)\\
\text{AdRos}: \quad & Ret_t - RF_t && = \alpha_{AdRos} + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SR} \cdot SR_t + \beta_{LR} \cdot LR_t && (3)\\
\text{AdRos4}: \quad & Ret_t - RF_t && = \alpha_{AdRos4} + \beta_{MKT} \cdot (MKT_t - RF_t) + \beta_{SR} \cdot SR_t && (4)\\
& && + \beta_{LR} \cdot LR_t + \beta_{FVIX} \cdot FVIX_t &&
\end{aligned}$$

FVIX is the factor-mimicking portfolio tracking changes in the VIX index. SR and LR are factor-mimicking portfolios tracking changes in short-run and long-run volatility forecast from Component GARCH model for the market factor, as in Adrian and Rosenberg (2008).

The columns of the table are labeled after the tests assets the models are fitted to. The test assets are quintile return spreads from sorts on profitability and gross profitability (from Table 3 in the paper) and on operating profitability, cash-based profitability and retained earnings divided by market value of equity (from Table 7 in the paper). The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2014. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

	Prof	**GProf**	**OProf**	**CProf**	**REarn**
$\boldsymbol{\alpha}_{CAPM}$	0.566	0.672	0.470	0.393	0.763
t-stat	*2.44*	*2.98*	*2.70*	*2.46*	*2.82*
$\boldsymbol{\alpha}_{ICAPM}$	0.000	0.159	0.234	0.146	0.383
t-stat	*0.00*	*0.71*	*1.33*	*0.92*	*1.48*
$\boldsymbol{\beta}_{FVIX}$	-1.226	-1.113	-0.515	-0.520	-0.829
t-stat	*-3.40*	*-3.15*	*-4.36*	*-5.14*	*-4.02*
$\boldsymbol{\alpha}_{AdRos}$	0.298	0.258	0.399	0.309	0.549
t-stat	*1.66*	*1.70*	*2.23*	*1.94*	*2.50*
$\boldsymbol{\beta}_{SR}$	-0.297	-0.216	-0.123	-0.107	-0.304
t-stat	*-8.22*	*-6.70*	*-2.88*	*-2.68*	*-6.44*
$\boldsymbol{\beta}_{LR}$	0.018	0.017	-0.001	0.004	-0.002
t-stat	*4.12*	*4.12*	*-0.33*	*1.36*	*-0.37*
$\boldsymbol{\alpha}_{AdRos4}$	0.152	0.163	0.251	0.200	0.466
t-stat	*0.90*	*0.96*	*1.39*	*1.26*	*1.96*
$\boldsymbol{\beta}_{SR}$	-0.260	-0.192	-0.085	-0.081	-0.283
t-stat	*-6.61*	*-5.21*	*-1.83*	*-2.01*	*-5.18*
$\boldsymbol{\beta}_{LR}$	0.016	0.015	-0.003	0.003	-0.003
t-stat	*3.68*	*3.80*	*-0.83*	*0.97*	*-0.69*
$\boldsymbol{\beta}_{FVIX}$	-0.388	-0.263	-0.388	-0.265	-0.232
t-stat	*-1.56*	*-1.25*	*-2.33*	*-2.26*	*-1.58*

Table 7A. Alternative Versions of FVIX

The table performs robustness tests by using alternative definitions of FVIX (Panel A-C) and repeating the main tests in the paper in the sample with stocks priced below $5 per share included (Panel D). Panel A presents descriptive statistics for three alternative versions of FVIX. FVIX90 uses only 1990-2014 data to form FVIX; FVIXT is a fully tradable version of FVIX formed using 1988-2014 and expanding window regression (1988-1990 are used as a training sample). FVIX6 is a version of FVIX that uses six size-BM porfolios as base assets. More detailed definitions of the alternative FVIX versions are in Section 9.1. Panel B presents correlations and partial correlations of the alternative FVIX versions. Partial correlations control the market return and are reported in italics below the main diagonal. Panel C presents CAPM alphas, as well as ICAPM alphas and FVIX betas from two-factor ICAPM with the market factor and alternative versions of FVIX used one after another. The test assets listed in the top row are quintile return spreads from sorts on profitability and gross profitability (from Table 3) and on operating profitability, cash-based profitability and retained earnings divided by market value of equity (from Table 7). Panel D repeats Panel B of Table 2 (explaining alpha of RMW) using FVIXT instead of FVIX. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2014. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Panel A. Descriptive Statistics

	Mean	**StDev**	**Sharpe**	$\boldsymbol{\alpha}_{CAPM}$	**Appraisal**	**Skew**	**Kurt**	$\boldsymbol{\alpha}_{FF5}$	**t-stat**
FVIX	-1.366	5.978	-0.229	-0.463	-0.337	1.003	6.203	-0.305	-3.731
FVIX90	-1.122	4.938	-0.227	-0.371	-0.349	0.697	4.407	-0.261	-3.602
FVIXT	-1.143	4.518	-0.253	-0.381	-0.398	0.630	4.473	-0.295	-3.971
FVIX6	-1.172	6.126	-0.191	-0.315	-0.186	0.774	5.029	-0.143	-2.044
FVIX500	-0.946	4.521	-0.209	-0.274	-0.347	0.737	4.517	-0.203	-3.418

Panel B. Correlations

	FVIX	**FVIX90**	**FVIXT**	**FVIX6**	**FVIX500**
FVIX		0.995	0.991	0.981	0.989
FVIX90	*0.936*		0.996	0.979	0.995
FVIXT	*0.853*	*0.919*		0.969	0.993
FVIX6	*0.732*	*0.723*	*0.590*		0.975
FVIX500	*0.841*	*0.889*	*0.843*	*0.690*	

Panel C. Profitability Anomaly and Alternative Versions of FVIX

	Prof	GProf	OProf	CProf	REarn
$\boldsymbol{\alpha}_{CAPM}$	0.566	0.672	0.470	0.393	0.763
t-stat	*2.44*	*2.98*	*2.70*	*2.46*	*2.82*
$\boldsymbol{\alpha}_{ICAPM}$	0.000	0.159	0.234	0.146	0.383
t-stat	*0.00*	*0.71*	*1.33*	*0.92*	*1.48*
$\boldsymbol{\beta}_{FVIX}$	-1.226	-1.113	-0.515	-0.520	-0.829
t-stat	*-3.40*	*-3.15*	*-4.36*	*-5.14*	*-4.02*
$\boldsymbol{\alpha}_{ICAPM90}$	0.159	0.167	0.252	0.250	0.465
t-stat	*0.65*	*0.85*	*1.37*	*1.57*	*1.66*
$\boldsymbol{\beta}_{FVIX90}$	-1.273	-0.915	-0.677	-0.456	-0.928
t-stat	*-2.30*	*-2.35*	*-3.99*	*-3.40*	*-3.47*
$\boldsymbol{\alpha}_{ICAPMT}$	0.226	0.299	0.198	0.296	0.323
t-stat	*0.91*	*1.74*	*1.07*	*1.87*	*0.98*
$\boldsymbol{\beta}_{FVIXT}$	-1.200	-0.656	-0.405	-0.381	-1.556
t-stat	*-2.30*	*-2.25*	*-2.19*	*-3.17*	*-3.08*
$\boldsymbol{\alpha}_{ICAPM6}$	0.169	0.186	0.303	0.239	0.482
t-stat	*0.91*	*1.13*	*1.77*	*1.52*	*2.05*
$\boldsymbol{\beta}_{FVIX6}$	-1.158	-0.812	-0.528	-0.469	-0.778
t-stat	*-6.56*	*-5.62*	*-4.99*	*-2.76*	*-3.87*
$\boldsymbol{\alpha}_{ICAPM500}$	0.258	0.268	0.198	0.322	0.394
t-stat	*1.01*	*1.58*	*1.07*	*1.94*	*1.29*
$\boldsymbol{\beta}_{FVIX500}$	-1.609	-0.898	-0.380	-0.411	-1.953
t-stat	*-2.69*	*-3.26*	*-1.78*	*-2.24*	*-3.13*

Panel D. Explaining RMW with FVIXT

	Raw	CAPM	ICAPM	FF	FF4	Carhart	5-factor
$\boldsymbol{\alpha}$	0.363	0.507	0.185	0.437	0.262	0.386	0.191
t-stat	*2.29*	*3.37*	*0.80*	*3.12*	*1.77*	*2.82*	*1.33*
$\boldsymbol{\beta}_{MKT}$		-0.219	-1.305	-0.145	-0.891	-0.130	-0.919
t-stat		*-4.17*	*-2.66*	*-2.91*	*-4.00*	*-3.02*	*-4.00*
$\boldsymbol{\beta}_{SMB}$				-0.320	-0.291	-0.325	-0.296
t-stat				*-3.01*	*-3.23*	*-2.92*	*-3.13*
$\boldsymbol{\beta}_{HML}$				0.220	0.261	0.243	0.281
t-stat				*2.13*	*3.22*	*2.50*	*3.60*
$\boldsymbol{\beta}_{MOM}$						0.064	0.065
t-stat						*1.16*	*1.39*
$\boldsymbol{\beta}_{FVIX}$			-0.948		-0.624		-0.672
t-stat			*-2.13*		*-3.07*		*-3.26*

Table 8A. Conditional CAPM and the Profitability Anomaly

Panels A1-C1 present average betas in recessions (β^{Rec}_{MKT}) and expansions (β^{Exp}_{MKT}), as well as their difference ($\Delta\beta_{MKT}$). The beta estimates are from the Conditional CAPM (CCAPM):

$$\begin{aligned} \text{CCAPM} : \text{Ret}_t - \text{RF}_t &= \alpha + \gamma_0 \cdot (MKT_t - RF_t) + \Gamma_1 \cdot Y_{t-1} \cdot (MKT_t - RF_t), && (5) \\ \beta_t &= \gamma_0 + \Gamma_1 \cdot Y_{t-1} && (6) \end{aligned}$$

where Y_t is the set of conditioning variables defined in the name of each panel. For example, Panel A estimates

$$\beta_t = \gamma_0 + \gamma_1 \cdot DEF_{t-1} + \gamma_2 \cdot DIV_{t-1} + \gamma_3 \cdot TB_{t-1} + \gamma_4 \cdot TERM_{t-1} \quad (7)$$

Panels A2-C2 present alphas and FVIX betas from the CAPM, ICAPM, and CCAPM, as well as the alphas and FVIX betas from the Conditional ICAPM (CICAPM):

$$\begin{aligned} \text{CICAPM} : \quad Ret_t - RF_t &= \alpha + \gamma_0 \cdot (MKT_t - RF_t) + && (8) \\ &\Gamma_1 \cdot Y_{t-1} \cdot (MKT_t - RF_t) + \beta_{FVIX} \cdot FVIX_t \end{aligned}$$

The test assets in the top row are quintile return spreads from sorts on profitability and gross profitability (from Table 3 in the paper) and on operating profitability, cash-based profitability and retained earnings divided by market value of equity (from Table 7 in the paper). The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2014. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Panel A. Conditional CAPM with DEF, DIV, TB, TERM

	A1. CCAPM Betas			**A2. Alphas, FVIX Betas, and Conditioning**					
	$\boldsymbol{\beta^{Rec}_{MKT}}$	$\boldsymbol{\beta^{Exp}_{MKT}}$	$\boldsymbol{\Delta\beta_{MKT}}$	$\boldsymbol{\alpha_{CAPM}}$	$\boldsymbol{\alpha_{CCAPM}}$	$\boldsymbol{\alpha_{ICAPM}}$	$\boldsymbol{\beta_{FVIX}}$	$\boldsymbol{\alpha_{CICAPM}}$	$\boldsymbol{\beta_{FVIX}}$
Prof	-0.195	-0.577	0.381	0.566	0.374	0.000	-1.226	-0.012	-0.925
t-stat	*-5.19*	*-15.0*	*6.74*	*2.44*	*1.86*	*0.00*	*-3.40*	*-0.06*	*-2.83*
GProf	-0.092	-0.442	0.350	0.672	0.296	0.159	-1.113	0.030	-0.636
t-stat	*-2.69*	*-11.9*	*6.69*	*2.98*	*1.80*	*0.71*	*-3.15*	*0.17*	*-2.77*
OProf	-0.088	-0.192	0.103	0.470	0.414	0.234	-0.515	0.265	-0.357
t-stat	*-3.01*	*-4.75*	*2.02*	*2.70*	*2.42*	*1.33*	*-4.36*	*1.47*	*-2.48*
CProf	-0.143	-0.261	0.118	0.393	0.325	0.146	-0.520	0.191	-0.321
t-stat	*-5.54*	*-9.21*	*3.01*	*2.46*	*2.04*	*0.92*	*-5.14*	*1.17*	*-3.31*
REarn	-0.101	-0.572	0.471	0.763	0.487	0.383	-0.829	0.228	-0.620
t-stat	*-3.71*	*-12.7*	*8.22*	*2.82*	*2.20*	*1.48*	*-4.02*	*1.01*	*-3.44*

Panel B. Conditional CAPM with DEF, DIV, TB, TERM, VIX

	B1. CCAPM Betas			**B2. Alphas, FVIX Betas, and Conditioning**					
	$\boldsymbol{\beta}_{MKT}^{Rec}$	$\boldsymbol{\beta}_{MKT}^{Exp}$	$\boldsymbol{\Delta\beta}_{MKT}$	$\boldsymbol{\alpha}_{CAPM}$	$\boldsymbol{\alpha}_{CCAPM}$	$\boldsymbol{\alpha}_{ICAPM}$	$\boldsymbol{\beta}_{FVIX}$	$\boldsymbol{\alpha}_{CICAPM}$	$\boldsymbol{\beta}_{FVIX}$
Prof	-0.222	-0.534	0.311	0.566	*0.373*	0.000	-1.226	-0.016	*-0.931*
t-stat	*-5.22*	*-13.0*	*5.34*	*2.44*	*1.85*	*0.00*	*-3.40*	*-0.07*	*-3.02*
GProf	-0.122	-0.416	0.294	0.672	0.295	0.159	-1.113	0.026	-0.644
t-stat	*-3.14*	*-10.3*	*5.40*	*2.98*	*1.77*	*0.71*	*-3.15*	*0.14*	*-3.16*
OProf	-0.103	-0.164	0.061	0.470	0.413	0.234	-0.515	0.264	-0.358
t-stat	*-3.25*	*-5.17*	*1.48*	*2.70*	*2.41*	*1.33*	*-4.36*	*1.46*	*-2.50*
CProf	-0.155	-0.226	0.070	0.393	0.325	0.146	-0.520	0.191	-0.321
t-stat	*-5.68*	*-9.18*	*2.05*	*2.46*	*2.03*	*0.92*	*-5.14*	*1.16*	*-3.29*
REarn	-0.109	-0.498	0.389	0.763	0.487	0.383	-0.829	0.228	-0.621
t-stat	*-3.56*	*-10.8*	*6.73*	*2.82*	*2.20*	*1.48*	*-4.02*	*1.01*	*-3.42*

Panel C. Conditional CAPM with DEF, DIV, TB, TERM, VIX, MKT(-1), MKT beta

	C1. CCAPM Betas			**C2. Alphas, FVIX Betas, and Conditioning**					
	$\boldsymbol{\beta}_{MKT}^{Rec}$	$\boldsymbol{\beta}_{MKT}^{Exp}$	$\boldsymbol{\Delta\beta}_{MKT}$	$\boldsymbol{\alpha}_{CAPM}$	$\boldsymbol{\alpha}_{CCAPM}$	$\boldsymbol{\alpha}_{ICAPM}$	$\boldsymbol{\beta}_{FVIX}$	$\boldsymbol{\alpha}_{CICAPM}$	$\boldsymbol{\beta}_{FVIX}$
Prof	-0.253	-0.528	0.275	0.566	0.351	0.000	-1.226	0.025	-0.813
t-stat	*-5.87*	*-8.05*	*3.56*	*2.44*	*1.75*	*0.00*	*-3.40*	*0.11*	*-2.72*
GProf	-0.160	-0.392	0.232	0.672	0.288	0.159	-1.113	0.050	-0.594
t-stat	*-4.44*	*-6.51*	*3.38*	*2.98*	*1.72*	*0.71*	*-3.15*	*0.26*	*-3.07*
OProf	-0.132	-0.140	0.008	0.470	0.442	0.234	-0.515	0.292	-0.375
t-stat	*-4.06*	*-4.46*	*0.20*	*2.70*	*2.54*	*1.33*	*-4.36*	*1.57*	*-2.65*
CProf	-0.161	-0.219	0.058	0.393	0.323	0.146	-0.520	0.195	-0.320
t-stat	*-5.70*	*-8.88*	*1.68*	*2.46*	*2.01*	*0.92*	*-5.14*	*1.18*	*-3.29*
REarn	-0.181	-0.432	0.251	0.763	0.503	0.383	-0.829	0.258	-0.610
t-stat	*-6.03*	*-7.31*	*3.73*	*2.82*	*2.29*	*1.48*	*-4.02*	*1.15*	*-3.38*

Table 9A. Distress Risk Puzzle and Average Idiosyncratic Volatility

Panels A and B report alphas from the CAPM, as well as alphas and FVIX betas from the ICAPM with the market factor and FVIX and alphas, FVIX betas, and FIVol betas from the volatility factor model (VolF) of Barinov and Chabakauri (2002). The models are fitted to profitability and gross profitability quintiles; market betas are not reported to save space. Profitability is net income before extraordinary items (Compustat ib item) divided by book value of equity (ceq plus txdb). Gross profitability is total revenue (sale) minus cost of goods sold (cogs) divided by book value of equity (ceq plus txdb). 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. FIVol similarly tracks monthly changes in average idiosyncratic volatility.

Panels C and D (E and F) report alphas and FVIX betas from the same three models fitted to returns to the healthy-minus-distressed strategy across O-score (idiosyncratic volatility) quintiles. The healthy-minus-distressed strategy is followed separately in each O-score (idiosyncratic volatility) quintile and involves buying the top profitability quintile and shorting the bottom profitability quintile. The profitability and O-score quintiles are formed using NYSE (exchcd=1) breakpoints and are rebalanced annually; idiosyncratic volatility are formed similarly, but are rebalanced monthly . The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2014. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Panel A. Profitability Quintiles

	Low	Prof2	Prof3	Prof4	High	H-L
α_{CAPM}	-0.366	0.068	0.147	-0.077	0.189	0.555
t-stat	*-1.90*	*0.71*	*1.76*	*-0.87*	*2.14*	*2.35*
α_{ICAPM}	0.088	0.122	0.125	-0.067	0.064	-0.025
t-stat	*0.48*	*1.23*	*1.39*	*-0.76*	*0.63*	*-0.10*
β_{FVIX}	0.979	0.101	-0.044	0.019	-0.272	-1.251
t-stat	*3.46*	*1.25*	*-0.47*	*0.24*	*-3.10*	*-3.56*
α_{VolF}	0.143	0.027	0.010	-0.036	0.097	-0.046
t-stat	*0.77*	*0.28*	*0.11*	*-0.43*	*0.93*	*-0.18*
β_{FVIX}	0.989	0.075	-0.071	0.026	-0.263	-1.252
t-stat	*3.65*	*0.79*	*-0.93*	*0.35*	*-2.68*	*-3.57*
β_{FIVol}	0.024	-0.071	-0.076	0.020	0.024	0.000
t-stat	*0.66*	*-3.74*	*-4.29*	*1.56*	*1.40*	*0.00*

Panel B. Gross Profitability Quintiles

	Low	GProf2	GProf3	GProf4	High	H-L
α_{CAPM}	-0.244	0.126	-0.035	0.121	0.198	0.442
t-stat	*-1.95*	*1.26*	*-0.33*	*1.50*	*2.23*	*2.42*
α_{ICAPM}	-0.032	0.175	0.022	0.009	0.041	0.073
t-stat	*-0.24*	*1.53*	*0.21*	*0.11*	*0.41*	*0.36*
β_{FVIX}	0.462	0.093	0.113	-0.239	-0.344	-0.805
t-stat	*2.91*	*1.04*	*0.98*	*-2.57*	*-2.92*	*-3.03*
α_{VolF}	-0.034	0.126	0.123	-0.010	0.042	0.076
t-stat	*-0.24*	*1.10*	*1.39*	*-0.12*	*0.40*	*0.36*
β_{FVIX}	0.459	0.079	0.135	-0.242	-0.343	-0.802
t-stat	*2.81*	*0.86*	*1.51*	*-2.65*	*-2.94*	*-2.98*
β_{FIVol}	-0.006	-0.039	0.066	-0.008	0.000	0.006
t-stat	*-0.26*	*-1.65*	*3.62*	*-0.53*	*0.00*	*0.17*

Panel C. Profitability Anomaly and Distress

	Low	O2	O3	O4	High	H-L
$\boldsymbol{\alpha}_{CAPM}$	0.002	0.048	0.139	0.099	0.758	0.756
t-stat	*0.02*	*0.32*	*0.83*	*0.56*	*2.12*	*2.50*
$\boldsymbol{\alpha}_{ICAPM}$	-0.199	-0.297	-0.235	-0.297	0.061	0.260
t-stat	*-1.23*	*-1.68*	*-1.33*	*-1.60*	*0.17*	*0.87*
$\boldsymbol{\beta}_{FVIX}$	-0.431	-0.737	-0.799	-0.845	-1.488	-1.057
t-stat	*-2.10*	*-3.78*	*-4.18*	*-3.39*	*-3.03*	*-3.25*
$\boldsymbol{\alpha}_{VolF}$	-0.282	-0.363	-0.268	-0.391	-0.134	0.148
t-stat	*-1.66*	*-1.90*	*-1.47*	*-2.04*	*-0.39*	*0.51*
$\boldsymbol{\beta}_{FVIX}$	-0.447	-0.747	-0.802	-0.866	-1.533	-1.085
t-stat	*-2.45*	*-4.17*	*-4.31*	*-3.93*	*-3.59*	*-3.78*
$\boldsymbol{\beta}_{FIVol}$	-0.050	-0.031	-0.007	-0.054	-0.120	-0.071
t-stat	*-1.50*	*-0.85*	*-0.24*	*-1.47*	*-2.14*	*-1.73*

Panel D. Gross Profitability Anomaly and Distress

	Low	O2	O3	O4	High	H-L
$\boldsymbol{\alpha}_{CAPM}$	0.435	0.396	0.464	0.277	0.921	0.486
t-stat	*2.78*	*2.20*	*2.34*	*1.52*	*4.10*	*2.68*
$\boldsymbol{\alpha}_{ICAPM}$	0.243	0.223	0.270	0.133	0.579	0.336
t-stat	*1.43*	*1.19*	*1.32*	*0.67*	*2.75*	*1.84*
$\boldsymbol{\beta}_{FVIX}$	-0.408	-0.371	-0.414	-0.307	-0.730	-0.321
t-stat	*-2.39*	*-3.42*	*-2.93*	*-2.43*	*-3.39*	*-2.87*
$\boldsymbol{\alpha}_{VolF}$	0.196	0.240	0.326	0.214	0.489	0.294
t-stat	*1.10*	*1.26*	*1.61*	*1.07*	*2.60*	*1.47*
$\boldsymbol{\beta}_{FVIX}$	-0.417	-0.364	-0.395	-0.287	-0.747	-0.330
t-stat	*-2.59*	*-3.13*	*-2.50*	*-2.18*	*-3.96*	*-3.00*
$\boldsymbol{\beta}_{FIVol}$	-0.028	0.019	0.052	0.057	-0.047	-0.019
t-stat	*-0.70*	*0.63*	*1.44*	*1.17*	*-1.19*	*-0.50*

Panel E. Profitability Anomaly and IVol

	Low	IVol2	IVol3	IVol4	High	H-L
$\boldsymbol{\alpha}_{CAPM}$	-0.021	0.341	0.343	0.145	0.881	0.902
t-stat	*-0.10*	*1.70*	*1.36*	*0.53*	*2.70*	*2.20*
$\boldsymbol{\alpha}_{ICAPM}$	-0.094	0.296	0.133	-0.099	0.320	0.415
t-stat	*-0.36*	*1.44*	*0.49*	*-0.34*	*1.00*	*0.85*
$\boldsymbol{\beta}_{FVIX}$	-0.156	-0.096	-0.448	-0.522	-1.197	-1.040
t-stat	*-0.62*	*-0.57*	*-1.78*	*-1.87*	*-1.87*	*-1.49*
$\boldsymbol{\alpha}_{VolF}$	0.127	0.343	0.122	-0.171	-0.067	-0.193
t-stat	*0.53*	*1.78*	*0.44*	*-0.56*	*-0.20*	*-0.41*
$\boldsymbol{\beta}_{FVIX}$	-0.105	-0.080	-0.446	-0.533	-1.285	-1.180
t-stat	*-0.40*	*-0.52*	*-1.76*	*-2.02*	*-2.59*	*-2.40*
$\boldsymbol{\beta}_{FIVol}$	0.144	0.045	0.002	-0.034	-0.242	-0.385
t-stat	*3.97*	*1.20*	*0.03*	*-0.62*	*-2.99*	*-4.63*

Panel F. Gross Profitability Anomaly and IVol

	Low	IVol2	IVol3	IVol4	High	H-L
$\boldsymbol{\alpha}_{CAPM}$	0.134	0.250	0.373	0.326	0.768	0.634
t-stat	*0.70*	*1.12*	*1.50*	*1.03*	*2.29*	*1.80*
$\boldsymbol{\alpha}_{ICAPM}$	0.025	0.239	0.336	0.063	0.374	0.349
t-stat	*0.12*	*1.01*	*1.22*	*0.18*	*1.10*	*0.91*
$\boldsymbol{\beta}_{FVIX}$	-0.219	0.021	-0.109	-0.462	-0.753	-0.533
t-stat	*-0.85*	*0.09*	*-0.27*	*-1.69*	*-1.73*	*-1.70*
$\boldsymbol{\alpha}_{VolF}$	0.093	0.370	0.372	0.103	0.151	0.058
t-stat	*0.43*	*1.46*	*1.40*	*0.27*	*0.44*	*0.16*
$\boldsymbol{\beta}_{FVIX}$	-0.219	0.012	-0.062	-0.541	-0.883	-0.664
t-stat	*-1.04*	*0.05*	*-0.19*	*-1.94*	*-2.23*	*-2.02*
$\boldsymbol{\beta}_{FIVol}$	0.045	0.095	0.043	0.045	-0.131	-0.176
t-stat	*1.40*	*2.19*	*0.94*	*0.89*	*-1.77*	*-2.48*

Table 10A. Duration vs. Volatility Risk: A Spanning Test

Panel A presents estimates of several factor models fitted to return to the duration factor, DUR. DUR is the return spread between bottom and top duration quintiles from Goncalves (2021). The factor models are the CAPM, the three-factor Fama and French (1993) model (FF3), the Carhart (1997) model, the five-factor Fama and French (2015) model (FF5), and the six-factor Fama and French (2016) model (FF6), as well as the versions of all those models augmented with FVIX (ICAPM, FF3+V, Carh+V, etc.). Panel B presents estimates of the same factor models, as well as their versions augmented with DUR, fitted to returns to FVIX. 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. Explaining the Alpha of the Duration Factor

	Raw	**CAPM**	**ICAPM**	**FF3**	**FF3+V**	**Carhart**	**Carh+V**	**FF5**	**FF5+V**	**FF6**	**FF6+V**
$\boldsymbol{\alpha}$	0.490	0.687	0.547	0.606	0.362	0.593	0.346	0.374	0.276	0.382	0.282
t-stat	*2.20*	*3.08*	*2.45*	*3.23*	*1.87*	*3.04*	*1.74*	*2.08*	*1.48*	*2.08*	*1.47*
$\boldsymbol{\beta}_{MKT}$		-0.282	-0.682	-0.288	-1.040	-0.284	-1.037	-0.205	-0.652	-0.207	-0.649
t-stat		*-4.28*	*-3.30*	*-4.75*	*-5.68*	*-4.73*	*-5.61*	*-3.81*	*-3.21*	*-3.87*	*-3.16*
$\boldsymbol{\beta}_{SMB}$				0.316	0.411	0.315	0.410	0.446	0.480	0.448	0.481
t-stat				*4.36*	*5.55*	*4.31*	*5.53*	*5.89*	*5.93*	*5.86*	*5.92*
$\boldsymbol{\beta}_{HML}$				0.260	0.220	0.267	0.228	0.098	0.109	0.086	0.102
t-stat				*2.88*	*2.59*	*2.92*	*2.65*	*1.18*	*1.22*	*1.12*	*1.24*
$\boldsymbol{\beta}_{MOM}$						0.017	0.020			-0.018	-0.009
t-stat						*0.35*	*0.44*			*-0.37*	*-0.20*
$\boldsymbol{\beta}_{FVIX}$			-0.302		-0.553		-0.555		-0.318		-0.314
t-stat			*-2.12*		*-4.19*		*-4.13*		*-2.29*		*-2.24*
$\boldsymbol{\beta}_{CMA}$								0.168	0.123	0.177	0.128
t-stat								*1.29*	*0.89*	*1.41*	*0.96*
$\boldsymbol{\beta}_{RMW}$								0.440	0.368	0.445	0.372
t-stat								*4.45*	*3.46*	*4.52*	*3.52*

Panel B. Explaining the Alpha of FVIX

	Raw	**CAPM**	**CAPM+D**	**FF3**	**FF3+D**	**Carhart**	**Carh+D**	**FF5**	**FF5+D**	**FF6**	**FF6+D**
$\boldsymbol{\alpha}$	-1.329	-0.462	-0.430	-0.440	-0.392	-0.445	-0.397	-0.307	-0.291	-0.320	-0.305
t-stat	*-4.65*	*-4.74*	*-4.89*	*-4.02*	*-4.11*	*-3.93*	*-4.08*	*-3.76*	*-3.85*	*-3.83*	*-3.94*
$\boldsymbol{\beta}_{MKT}$		-1.325	-1.338	-1.358	-1.381	-1.357	-1.380	-1.408	-1.417	-1.404	-1.412
t-stat		*-36.8*	*-40.9*	*-35.0*	*-40.8*	*-33.8*	*-39.9*	*-50.4*	*-54.7*	*-48.9*	*-53.2*
$\boldsymbol{\beta}_{SMB}$				0.171	0.196	0.170	0.195	0.107	0.126	0.104	0.123
t-stat				*4.95*	*5.26*	*5.09*	*5.41*	*4.58*	*4.59*	*4.72*	*4.71*
$\boldsymbol{\beta}_{HML}$				-0.073	-0.052	-0.070	-0.049	0.034	0.038	0.052	0.056
t-stat				*-1.40*	*-1.04*	*-1.41*	*-1.00*	*0.59*	*0.64*	*0.85*	*0.89*
$\boldsymbol{\beta}_{MOM}$						0.006	0.007			0.027	0.026
t-stat						*0.34*	*0.43*			*1.54*	*1.57*
$\boldsymbol{\beta}_{DUR}$			-0.046		-0.079		-0.079		-0.042		-0.041
t-stat			*-1.85*		*-2.87*		*-2.86*		*-1.76*		*-1.75*
$\boldsymbol{\beta}_{CMA}$								-0.142	-0.135	-0.156	-0.149
t-stat								*-2.30*	*-2.19*	*-2.48*	*-2.38*
$\boldsymbol{\beta}_{RMW}$								-0.225	-0.207	-0.233	-0.215
t-stat								*-6.18*	*-5.87*	*-6.33*	*-6.04*

Table 11A. Duration vs. Volatility Risk as Explanations of the Profitability Anomaly

The table presents estimates of several factor models fitted to return to the Fama and French profitability factor, RMW. The factor models are the CAPM, the three-factor Fama and French (1993) model (FF3), the Carhart (1997) model, and the ICAPM with the market factor and FVIX, as well as their versions augmented with DUR factor (ICAPM+D, FF+D, Carh+D) or augmented with both DUR and FVIX (FF+D+V, C+D+V). DUR is the return spread between bottom and top duration quintiles from Goncalves (2021). 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.

	Raw	**CAPM**	**CAPM+D**	**ICAPM**	**ICAPM+D**	**FF3**	**FF+D**	**FF+D+V**	**Carhart**	**Carh+D**	**C+D+V**
$\boldsymbol{\alpha}$	0.353	0.494	0.413	0.108	0.064	0.430	0.327	0.121	0.386	0.286	0.076
t-stat	*2.42*	*3.54*	*3.49*	*0.65*	*0.42*	*3.28*	*2.73*	*1.05*	*3.03*	*2.51*	*0.68*
$\boldsymbol{\beta}_{MKT}$		-0.216	-0.183	-1.322	-1.267	-0.144	-0.095	-0.818	-0.129	-0.081	-0.811
t-stat		*-4.26*	*-4.27*	*-3.68*	*-3.44*	*-2.97*	*-2.14*	*-4.32*	*-3.09*	*-2.22*	*-4.26*
$\boldsymbol{\beta}_{SMB}$						-0.318	-0.371	-0.269	-0.320	-0.373	-0.270
t-stat						*-3.09*	*-3.71*	*-3.30*	*-2.98*	*-3.55*	*-3.16*
$\boldsymbol{\beta}_{HML}$						0.209	0.165	0.138	0.232	0.187	0.161
t-stat						*2.11*	*1.90*	*1.82*	*2.48*	*2.31*	*2.23*
$\boldsymbol{\beta}_{MOM}$									0.058	0.055	0.059
t-stat									*1.08*	*1.04*	*1.21*
$\boldsymbol{\beta}_{DUR}$			0.118		0.080		0.170	0.128		0.168	0.126
t-stat			*2.17*		*1.69*		*3.67*	*3.14*		*3.69*	*3.22*
$\boldsymbol{\beta}_{FVIX}$				-0.835	-0.810			-0.524			-0.529
t-stat				*-3.23*	*-3.08*			*-3.88*			*-3.91*